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The Brazilian Air Force health system workforce-needs estimation using system dynamics

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THESIS

THE BRAZILIAN AIR FORCE HEALTH SYSTEM: WORKFORCE-NEEDS ESTIMATION USING SYSTEM DYNAMICS

by

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March 2009

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THE BRAZILIAN AIR FORCE HEALTH SYSTEM: WORKFORCE-NEEDS ESTIMATION USING SYSTEM DYNAMICS

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ABSTRACT

The demand for physician manpower is a function of the demand on the entire health system, which varies as a function of user demographic characteristics. The recruit quantity and the departure behavior over time cause oscillations in the actual quantity and in the services system quality. These aspects are related with each other and exogenous systems lead the health system to behave as a complex structure. This thesis defines a preliminary system-dynamics model that analyzes and forecasts Brazilian Air Force health-system physician demand and its estimated effect on the required number of medical professionals.

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EXECUTIVE SUMMARY

The demand for physician manpower is a function of the demand on the entire health system, which varies as a function of user demographic characteristics. These characteristics differ among countries and may exhibit large imbalances within a country. Demographic imbalances can be found throughout Brazilian society and consequently are present in the Brazilian Air Force (FAB) which health systems conventionally follow a user-driven demand for physicians.

Actions resting on assumptions about future demand on the health system not only affect system performance, but also are essential to recruitment and retention policies and decisions. Forecasting methodology must be developed and constantly improved to minimize its limitations by enabling dynamic analysis and identification of delayed-feedback effects.

The increasing trend in the FAB user population follows a worldwide pattern, driving physician demand and raising concerns about effective health services in the future. Maintaining the level of FAB health services is an urgent problem. This research works towards solving this problem and improves understanding of health-system behaviors and interactions with other FAB systems by showing the causations, delays, and feedback created by manpower-management policies.

This research used thirty years of data to capture the full length of a physician's career in the FAB and to predict behavior over the next thirty years; i.e., the focal timeline is 1978–2038. This long horizon permits a deeper understanding of the factors that affect the system and interactions among them and with other systems, considering a variety of recruiting and retention policies and career decisions made by medical professionals. With this data, manpower policies can be simulated in different scenarios, providing a new instrument for determining the number of physicians that should be recruited each year.

The FAB was born with the Brazilian Air Force in 1941, when naval and army aviation merged. On that occasion, thirty-four army, ten naval, and five civilian

physicians became Brazilian Air Force physicians. In December of that year, the Brazilian government created the Brazilian Air Force health community with eighty physicians. Temporary officers, those who remain in the military for a limited time, were designated in June 1967 as an alternative way to recruit physicians. Both officer types, career and temporary, are allocated within Brazilian boundaries.

The FABHS is formed by a synergistic composition of numerous health professionals, predominantly physicians, dentists, and pharmacists. The health system users are military members and their dependents and changes in the numbers of users will lead changes in the same direction in the quantity of physician needed. The GAP, i.e., the difference between needs and the actual physician quantity affects the hiring policies.

Logically, changes in the hiring quantity will reflect in changes in the same direction to physician quantity that leads to changes in the same direction in the quantity of physicians that leave the system each year, which causes the GAP.

Manpower planning is a synergistic mix of tools to aid future planning views. The integration between design, creativity, and complexity, when well done, leads to a better understanding of the system. The most effective method of forecasting manpower is dynamic-system modeling supported by stochastic techniques and comparative-analysis methodologies.

The description and behavior prediction of large groups of people is the main concern of manpower planning and a mathematical-modeling approach is well suited; although individual behavior is unpredictable, the data follow statistical patterns when aggregated.

So, a stochastic model of manpower systems is a probabilistic description of the interrelationships between stocks and flows of manpower over time and it could be defined by the probability distribution of the number of “entrees and leavers” per year.

As a mix of stocks and flows, the manpower system is managed as a supply chain, coordinating the demand, supply, development, and inventory of the workforce. Thus, manpower planning must be able to develop and deploy the right people at the right place at the right time in order to fulfill both organizational and individual objectives.

A logistic regression model of the departure behavior was used to get the probability of outflow from the system, which becomes more complex when the causal effects take place.

The FABHS structure is affected by the flow of physicians, user demand, physician productivity, and delays that trigger decisions that will shape the system's behavior. The behavior of complex systems—where many disciplinary fields come together—can be predicted by nonlinear models and feedback control that are related to mathematics, physics, and engineering. An interdisciplinary tool grounded in those fields is the key to enhanced learning in complex systems, and this is what system dynamics is all about. Just as flight simulators help pilots learn to fly, system dynamics help decision makers learn about the complexity of system dynamics and how to design effective policies.

This research explores two scenarios in a way to predict recruitment numbers, physician stock and their departure behavior over time. The first is based on market favorable for supplying the military with physicians needed and the second scenario uses the recruitment quantity for temporary officers and the last desired recruitment quantity defined for the national exam for career officers, assuming that the supply physician market has enough physicians to fulfill the desired calculated quantity.

One of the outcomes of this research is the understanding of how physicians in the Brazilian health system behave over time. System-dynamics modeling, together with multivariate regression, allows the model to receive physician behavior and predict behavior and recruitment trends for the next thirty years.

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Completing a thesis towards a master's degree is an effort that is impossible to accomplish alone, and as a modeling student I first modeled a strategy for this achievement in my heart. I began by asking wisdom and guidance from our powerful God to help me structure my life. Second, I relied on my family as my main support throughout this endeavor, though I was constrained to leave them literally alone while I spent days in research and thought, increasing my stock of knowledge. Third, I used the precious advice of my mentors to establish the connections and feedbacks of the whole system. Finally I let the model run and time pass in order to see the desired outcome, this thesis.

I thank God for giving me the resources I needed to reach this goal, and with all my heart I offer both my achievement and its rewards to my wife, Luciana, and sons, Gabriel and Guilherme. Thank you to my advisers, professors Ferrer and Tarek, for their knowledge, wisdom, time, and guidance during this voyage. And thanks to my senior officers and friends from the Brazilian Air Force who helped me be here and do this work.

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I. INTRODUCTION

A. THE PROBLEM

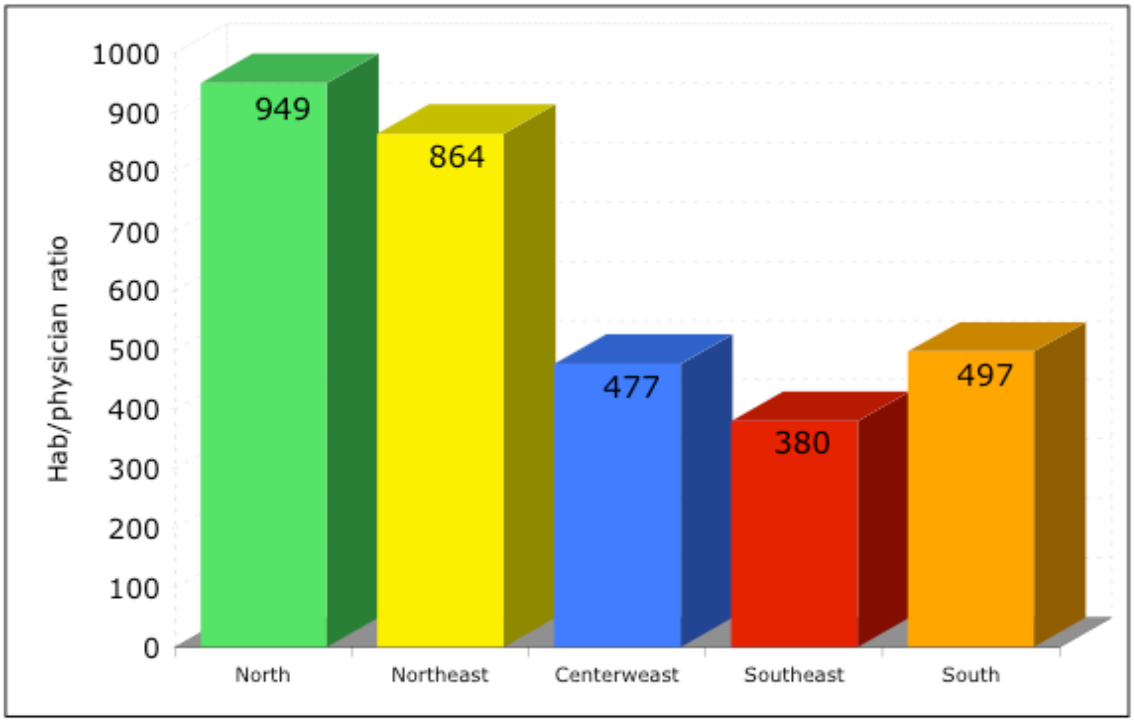
The World Health Organization (WHO) defines a health system as the sum of the organizations and resources whose primary purpose is to improve the health of a general population. There is worldwide interest among governments and health organizations in providing efficient health services. In this research, efficiency translates to providing desired health services using available resources without waste and in the best possible manner—more precisely, using physician manpower in such a way as to satisfy need and provide a sustainable health service.

The demand for physician manpower is a function of the demand on the entire health system, which varies as a function of user demographic characteristics. These characteristics differ among countries and may exhibit large imbalances within a country. Such is the Brazilian case, as shown in Figure 1. Brazil is the fifth largest country in territorial size and has significant differences amid its various regions, including differing cultural features and demographic distributions. Demographic imbalances can be found throughout Brazilian society and consequently are present in the Brazilian Air Force (FAB), which conventionally follow a user-driven demand for physicians.

Because the health-system users of the FAB are military members and their families, there is a significant yearly increase in users due to recruitment, marriage, and birth.

Planning for future manpower needs must factor in this increasing number, which will, to some degree, affect the quality and the extent of services offered. Capacity needs must be identified very early, allowing time to recruit and train young medical professionals until they can become fully productive within the organization. As time unfolds, uncertainties regarding forecasted demand gradually dissipate and developments may occur that alter previous estimations of manpower need. At the same time, though decisions made when confronting an imbalanced workforce normally do not solve the gap problem, they may improve it in function of the delays present on the system. These factors add up to a complex and dynamic manpower system.

Figure 1 Number of inhabitants per physician per region



Source: Brazilian Health Minister, Human Resources System Information (SIRH-2007).

Manpower policy decisions affect the overall system, causing concerns about the future such as,

- How will FAB manpower structure be affected if the demand for physicians is, or is not, fulfilled?
- What is the opportunity cost to fulfill, or not fulfill, the need for physicians?

Actions resting on assumptions about future demand on the health system not only affect system performance, but also are essential to recruitment and retention policies and decisions. The practice of forecasting and making decisions under the assumption that the future will be like the past is a common procedure for determining manpower needs in the FAB. Forecasting methodology must be improved to minimize its limitations by enabling dynamic analysis and identification of delayed-feedback effects.

The results from a good model are not primarily useful in anticipating or reacting to problems, but in obviating them by changing the complex structure of the system. In summary, a good methodology to forecast the FAB health-system workforce must take into consideration the dynamic interactions between the variables involved.

B. RESEARCH PURPOSE

The World Health Organization Statistical Information System (WHOSIS) shows an increase in the Brazilian population while the number of physicians has remained constant, thereby increasing the population/physician ratio. The World Health Organization defines a 1,000/1 ratio as desirable. The Brazilian population in 2000 was about 189,323,000 inhabitants, and in that year there were approximately 198,153 active physicians, yielding an average population/physician ratio of 955/1—close to the target ratio.

The trend in the FAB user population follows a worldwide pattern, driving physician demand and raising concerns about effective health services in the future. FAB has raised medical-recruitment levels in view of this trend and to reduce the gap between the need for service and the actual stock of physicians. However, this policy faces constraints such as limitations imposed by law, the physical capacity of training facilities, the supply of physicians, and so on.

Maintaining the level of FAB health services is an urgent problem. Yet there exists almost no research to analyze the effectiveness of recruitment strategies and to predict system behavior over time. This research works towards solving this problem and improves understanding of health-system behaviors and interactions with other FAB systems by showing the causations, delays, and feedback created by manpower-management policies.

C. RESEARCH OBJECTIVE

The primary objective of this research is to understand the dynamic behavior of the Brazilian Air Force health system (FABHS) over time. This research will use thirty years of data to capture the full length of a physician's career in the FABHS and to predict behavior over the next thirty years; i.e., the focal timeline is 1978–2038. This long horizon permits a deeper understanding of the factors that affect the system and interactions among them and with other systems, considering a variety of recruiting and retention policies and career decisions made by medical professionals. With this data, manpower policies can be simulated in different scenarios, providing a new instrument for determining the number of physicians that should be recruited each year.

D. RESEARCH QUESTIONS

The research aims to answer the primary question: What physician-manpower policy will effectively support FABHS needs?

Additionally, the following questions are raised:

- How can trends in short- and long-term demand in the FABHS be measured?
- What are the annual trends for physician headcount?
- How do interactions among physician characteristics affect system behavior?

E. BACKGROUND

1. Physician Overview

In 2002, the Brazilian health minister published a regulation (Port. n.º 1101/GM) that determined the overall performance targets for the government health system (SUS). This regulation directs sectors that are engaged in public health to respect these targets in determining workforce needs for each hospital. These targets are adopted in this research as a starting point to define the minimum medical workforce need for the military.

Brazilian law n° 3.999 of December 15, 1961, states that a physician must work no more than four hours per day. This limitation shapes physician availability and productivity. The FAB health system must have enough physicians to keep health services continuously operational in accordance with required service levels for every hospital of every region.

The duration of the average medical visit is an important variable that needs to be defined. Some Brazilian researchers cite a minimum of fifteen minutes for a good-quality preliminary examination; others cite twenty minutes. For this research, the initial assumption is fifteen minutes, which will vary during dynamic simulation of different scenarios.

Table 1 Medical Visits per User per Year

Region	2001	2003	2005
All	2.4	2.5	2.5
North	1.6	1.8	2.0
Northeast	2.2	2.3	2.2
Southeast	2.8	2.9	2.9
South	2.4	2.4	2.3
Center-West	2.4	2.4	2.4

Source: Brazilian Health Minister/DATASUS.

The number of medical visits per capita is in the range of two-to-three visits per year, but varies according to region. The number of medical visits per user for each region was obtained from the health-ministry information system—DATASUS—and reflects the overall population, from which FABHS users are a sample. Table 1 summarizes the respective rate. The number of medical visits per capita measures the average number of medical visits per user for each region in odd years. This variable is known to be affected by socioeconomic factors and epidemiological and demographical variables such as age composition, physician supply, etc. This variable is helpful in measuring physician productivity and its relation to user demand.

2. The Military Physicians at a Glance

The FABHS was born with the Brazilian Air Force in 1941, when naval and army aviation merged. On that occasion, thirty-four army, ten naval, and five civilian physicians became Brazilian Air Force physicians.

In December of that year, the Brazilian government created the Brazilian Air Force health community with eighty physicians. Temporary officers, those who remain in the military for a limited time, were designated in June 1967 as an alternative way to recruit physicians. Both officer types, career and temporary, are allocated within

Brazilian boundaries. The law allows the flexibility of recruiting physicians within their home region, but precludes temporary officers from staying with the force for more than ten years.

The administrative regions of the Brazilian Air Force are responsible for managing the physician-workforce inventory within their boundaries. Each region has its unique physical and cultural characteristics. Regions with low population density provide a low supply of physicians.

The FABHS is formed by a synergistic composition of numerous health professionals, predominantly physicians, dentists, and pharmacists, representing a large number of officers. These officers are contracted as either reserve or career officers, both categories being active duty.

Temporary physicians primarily support the physician-workforce shortfall. The temporary workforce is culled from the initial military service, or draft, which recruits from the civilian-physician pool. Upon turning eighteen, all men are required to register for military service as reservists. If attending medical, dental, or pharmaceutical school, the draftee is allowed to delay service until after graduation. The status of temporary physician is also open for volunteers (of both genders) who complete a health-related college degree (medical, dental or pharmaceutical school). A temporary appointment may be renewed annually for a maximum of eight years. At any time, the temporary officer may take a national exam to transfer to the career-officer ranks. This exam is offered to all citizens once a year to select career officers. They must be Brazilian citizens (men or women) and have graduated from an accredited medical, dental or pharmaceutical school.

The number of health officers (reserve and career) selected depends on anticipated need for physicians and the number of applicants in each category. However, this requirement is also constrained by individual career progression through the military ranks, leading to a decrease in retention. If the FAB does not attract enough voluntary applicants, it may require men to perform compulsory service as temporary officers upon graduation from medical, dental, or pharmaceutical school. Thus the number of candidates approved in the national exam needs to increase to match the inventory level of health officers. This creates a challenge for managing promotion flow, normally increasing the time it takes to move up the ranks and consequently resulting in more attrition and less retention. It is important to emphasize that recruiting numbers are based on the active-personnel attrition rate.

Finally, the FABHS is a closed personnel system, i.e., it hires at the entry point those with (normally) no military experience and provides all training necessary to promote from within. This internal labor market is divided for career officers into two main groups, junior and senior officers. Junior officers are those with fewer than fifteen years' experience and include the ranks of lieutenant and captain. Senior officers have more than fifteen years in the military and include the ranks of major, lieutenant colonel, and colonel.

3. Users of the Brazilian Air Force Health System

FABHS users are military members and their dependents. The military members became users automatically when they join the military. Dependents are normally a spouse, sons younger than twenty-one, and unmarried daughters. The system may allow the inclusion of other relatives as defined by law.

The ratio of dependents per military is on average .52, i.e., almost one dependent per each two militaries. Every year, there is a significant increase in the number of users through recruitment, marriage, birth, and so on. This trend is the main concern related to quality of service. Although those who leave the system decrease the user population, it is important to emphasize that medical-recruitment numbers are based on active-personnel attrition. Nevertheless, this process is imbalanced for an important reason: retired militaries remain users of the health system until death, and so do their dependents, and this is where the main problem arises. Resulting imbalances, and the need to match the supply of health specialists with user need (population demand), are brought on by the increase in population. This may cause the health system to fail from dearth of health professionals in the near future.

Figure 2 and Table 2 summarize the Brazilian Air Force health system user distribution by administrative regions.

Figure 2 Brazilian Air Force administrative regions

Table 2 User Distribution

Region	Number of Users
Comar I	4948
Comar II	57503
Comar III	144193
Comar IV	45097
Comar V	30440
Comar VI	39370
Comar VII	18935
Total	340483

Source: Brazilian Air Force Personnel-Command Statistics System

Currently, as more users attempt to use the health system, physicians must maintain an adequate visitation time close to the minimal acceptable duration. The increase in users requires an increase in the number of physicians; otherwise an increase in waiting time and a consequent increase in the amount spent in visits outside the system will result.

F. DYNAMIC HYPOTHESIS

Sterman (2000 p.94) states that once a researcher indentifies a problem and defines an appropriate time horizon, a dynamic hypothesis theory must be developed. System-dynamics modeling is way to understand how a complex system continually corrects itself over time until it reaches some kind of equilibrium.

The hypothesis is first conceptualized in terms of a causal-loop diagram (Figure 3) where a preliminary architecture of the model represents a simple view of FABHS. Sterman (2000 p.102) comments that causal-loop diagrams are flexible and useful tools that permit the visualization of feedbacks and causal links among variables.

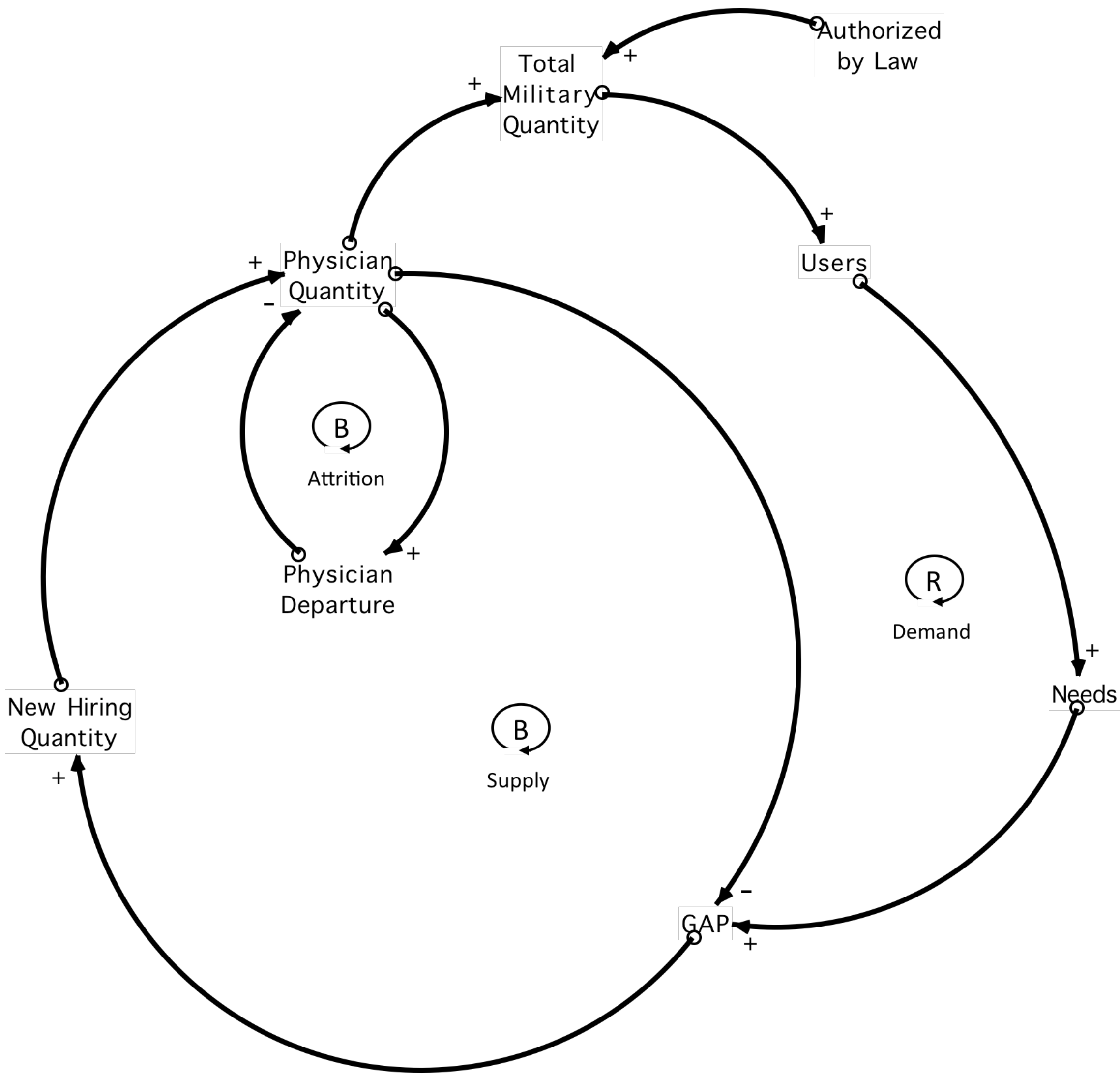
The causal-loop diagram shows that changes in *Physicians Quantity* occur in the same direction as changes in *Total Military Quantity*, which is limited by *Authorized by Law*. Since they change in the same direction, they are said to be reinforcing (**R**). Common sense says that there is a relationship between *Total Military Quantity* and the number of health-system users: changes in *Total Military Quantity* occur in the same direction as the number of *Users*.

Through experience, it is easy to recognize that changes in the number of users will reflect in changes in the same direction in *Needs*, which can be compared with *Physicians Quantity* leading to changes in the same direction in *GAP*.

The *GAP*, i.e., the difference between *Needs* and *Physician Quantity* affects the *New Hiring Quantity* introduced each year in the same direction and is affected by changes in *Physician Quantity* in the opposite direction. This loop is said to be balancing **(B)**.

Logically, changes in *New Hiring Quantity* will reflect in changes in the same direction to *Physician Quantity*. Additionally, changes in *Physicians Quantity* lead to changes in the same direction in the number of *Physician Departure* from the system, reflecting in changes in *Physicians Quantity* in the opposite direction, another balancing loop.

Figure 3 A causal-loop diagram of the FAB health system



II. LITERATURE REVIEW

A. MANPOWER PLANNING

Manpower planning is a synergistic mix of tools to aid future planning views. The integration between design, creativity, and complexity, when well done, leads to a better understanding of the system, i.e., knowledge of its qualities in relation with other systems and the implications of past and future decisions.

Alan Yelsey (1982) grouped human-resources forecasts into the following classifications:

1. **Actuals** Actuals predict the size of workforce, with whatever characteristics, that will exist at a given time. Prediction can be done by gender, age, skills, region, or any other characteristic, but the aim is to provide as accurate an actual number as possible in a given period.
2. **Dynamic systems** Dynamic systems predict the life movements of a workforce within a closed system and its interactions with other systems. Movements are quantifiable, as rates of flow and outflow of hires, deaths, transfers, and promotions. The results are not an accurate number of people at a given time, but rather a trend, as well as knowledge about the dynamics of the workforce in the system.
3. **Non-intervention** This forecast provides a potential scenario of workforce numbers, based solely on actual numbers derived from present knowledge and actions taken under the assumption that no unexpected interventions will occur. It is a red flag that guides future decisions.
4. **Value added** This category measures the workforce not as a headcount, but as resources. It quantifies by measuring variables such as age, skills, gender, ethnicity, skills, and performance. It sees the workforce as capital—a value-added approach to inventorying people.

Yelsey comments that the most effective method of forecasting manpower is dynamic-system modeling supported by stochastic techniques and comparative-analysis methodologies.

McClean (1988) points out that the description and behavior prediction of large groups of people is the main concern of manpower planning. She recalls that a mathematical-modeling approach is well suited; although individual behavior is unpredictable, the data follow statistical patterns when aggregated.

Stochastic models differ from deterministic models by including randomness and thus have variables with values that could be represented as a distribution. Bartholomew (1974) establishes a stochastic model of manpower systems as a probabilistic description of the interrelationships between stocks and flows of manpower over time. Thus, for example, the probability of a physician leaving the military given that he has j years of service and i years of age is w_{ji} and this is used for all physicians with j years of service and i years of age. This statement enables one to determine the probability distribution of the number of "leavers" in any year, in that if there are n_{ji} physicians in stock in a given year then the expected number of leavers is $n_{ji}w_{ji}$ physicians.

As a mix of stocks and flows, the manpower system is managed as a supply chain, coordinating the demand, supply, development, and inventory of the workforce. Walker (1974) suggested that manpower planning must be able to develop and deploy the right people at the right place at the right time in order to fulfill both organizational and individual objectives. Walker (1971) also affirms that multiple-regression models, which permit variables to be considered together in the projection of an event, can appropriately model manpower-systems behavior in some situations.

Stokey and Zeckhauser (1978) define stock as the total number of individuals and flow as additions or subtractions from stock in each period. Stock is measured in units, e.g., a physician, and the flow is the change in stock over time. They synthesize the fundamental relationship between stock and flow as $S_{t+1} = S_t + I_t - O_t$, where S is the current stock, *I* the inflow, and *O* the outflow. Thus, stock is the number of practicing military physicians; inflow is new physicians recruited; and outflow is the sum of retirements, departures, and deaths.

Inflow to the system, i.e., the number of physicians recruited per unit of time, is a partially controlled variable that is a function of the number of users and physician productivity. The system outflow (retirements, departures, and deaths) is a function of exogenous factors that are, by their nature, random. Stokey and Zeckhauser (1978) observe that the flow variable needs to be the primary target of policy concern.

Christie Teigland and Lori Hewig (1990), while developing research for the New York state government, address some questions for forecasting human-resources needs, transcript here with adaptation: How many physicians are likely to retire from military service? How many physicians are likely to resign? How many physicians increase the attrition statistics? What characterizes physician-departure behavior?

The departure rate is one the main variables affecting inventory control. When physician inventory is reduced by unpredicted departure, there is an expected increase in the disparity between recent and new inventory workforce levels and some years of delay in returning inventory to previous levels—thus causing significant impact on the quality of the health system. The departure rate plays a part in the shortage problem, and efforts to improve retention must be informed by an understanding of the factors that contribute to these departures.

The departure behavior for a cohort, as outflow from the system, can be expressed as a function of average physician age, average time of service or experience, and gender and ethnicity distribution. Many other factors can affect the departure ratio, and future research must measure these factors to allow for more precise models.

Physician age, as a function of the labor market, drives the decision of staying or leaving. Internal data shows that external opportunities increase with younger age and decrease with older age. Experience, expressed as length of service in the military, affects the decision to leave because the external market values medical professionals with more experience.

The overall temporary-officer gender distribution for recent cohorts is almost 80% female, i.e., the supply market for temporary physicians is made almost completely of female volunteers. The departure behavior is different for each gender.

Ethnicity is another variable that seems to influence departure behavior. Ethnicity is here defined as white, black, or multi-ethnic. A large portion of the population is characterized by different combinations of white, black, and native Brazilian ethnicity, as shown in Table 3.

Table 3 Total population and distribution by ethnicity and region

Region	**Total**	**Ethnicity (%)**			
		White	*Black*	*Mix*	*Other*
North	9 795 161	28,0	4,7	66,8	0,4
Northeast	49 768 896	30,3	5,4	63,9	0,4
Southeast	78 975 768	63,2	6,7	29,4	0,7
South	27 904 546	82,7	3,7	13,1	0,5
Center west	13 553 681	44,6	4,3	50,1	1,0
Total	179 998 052	53,3	5,6	40,5	0,6

Source: Brazilian Geography and Statistic Institute (IBGE)

Data shows that these variables (age, experience, gender, and ethnicity) correlate dynamically with departure behavior, adding complexity to the modeling, planning, and prediction process.

B. MANPOWER-PLANNING TOOLS

According to Vadja (1984), the earliest manpower planning used in predicting population behavior was realized by Graunt (1662), in a document called "Bills of Mortality."

It is common sense that physician-manpower planning is concerned with allocating the right number of doctors to fulfill system needs with the right specialty, in the right place, at the right time. This is not identical to personnel management, which must take intimate account of an individual's career, but it looks at the overall purposes of the system as well as potential changes that could affect the system over time.

The Brazilian Air Force's general personnel command (COMGEP) plans physician manpower by using tools that include recruitment, promotion, transfer, and departure policies. The results of these tools are influenced by the market supply of physicians, demographics, and regional epidemiology.

Recruitment is based on filling vacancies opened by departures. So the first important factor to be measured is departure behavior.

1. Multivariate Analysis

According to Hair (1998), multiple-regression analysis is a statistical tool that can be used to analyze the relationship between a single dependent (criterion) variable and several independent (predictor) variables. The main objective of a multivariate-regression analysis is to use independent variables whose values are known to predict a single dependent variable. Wooldridge (2006) recalls that the better models for predicting dependent variables are based on multiple-regression analysis.

Thus, $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u$, where "$y$" represents the dependent variable, "β_0" the intercept, "β_k" is the parameter associated with "x_k" and the variable "u" is the error term or disturbance. This last variable contains all factors beyond "x_k". Wooldridge (2006) reminds that no matter how many predictors are included in the model, there will always be factors that cannot be included and these are collectively contained in "u".

The "y" or dependent variable in our model is the departure event, which has a relationship with age, experience, gender, ethnicity, and other factors that have not been measured yet. So the departure event can be written as a function of f (age, experience, gender, ethnicity), as showed in the formula:

$$departure = \beta_0 + \beta_1 age + \beta_2 experience + \beta_3 gender + \beta_4 ethnic + other\_fct$$

Since departure is an absolute event that may or may not occur, it may be characterized with value equal to one for those who have already left the system and zero otherwise. Stock and Watson (2007) comment that this type of variable is generically called a dummy variable because in an econometric model, a dummy variable marks or encodes a particular attribute. Clemen and Reilly (2001) describe this type of variable as categorical and conclude that, given the value of predictors, it is possible to specify the conditional probability of falling into that category. Agresti (p.120, 2002) declares that a response for categorical dependent variables changes the regression model to $\pi\left(departure\right) = \beta_0 + \beta_1 age + ... + \beta_4 ethnic$, where $\pi\left(departure\right)$ is the probability of departure, and the model is called a linear probability model.

Clearly, there is no linear relation between "x_k" and $\pi\left(departure\right)$, because although "$x_k$" may vary substantially, $\pi\left(departure\right)$ is limited to the interval (0,1). For example, the probability of departure decreases with age. However, the change in probability between physicians that are twenty-eight and twenty-nine years old is greater than between physicians that are forty-eight and forty-nine years old. Agresti (p. 121, 2002) confirms that, usually, binary data result from a nonlinear relationship between $\pi\left(departure\right)$ and "x_k" and adds that in practice, nonlinear relationships between predictors and dependent variables are often monotonic, with $\pi\left(departure\right)$ increasing continuously or decreasing continuously as "x_k" increases. Considering these limitations, the following asymptotic model represents this behavior:

$$\pi\left(departure\right) = \frac{exp(\beta_0 + \beta_1 age + ... + \beta_4 ethnic)}{1 + exp(\beta_0 + \beta_1 age + ... + \beta_4 ethnic)}$$

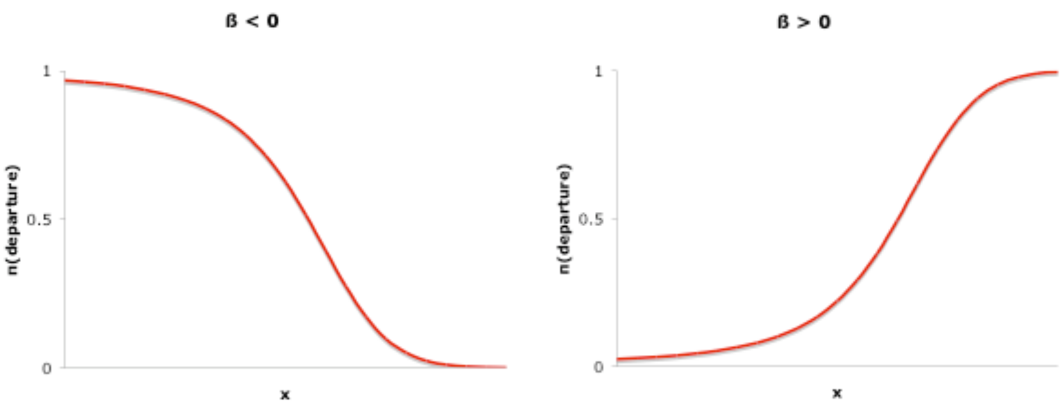
This model is a logistic-regression model and could be simplified to,

$$\text{logit}\left[\hat{\pi}\left(departure\right)\right] = \beta_0 + \beta_1 age + \beta_2 experience + \beta_3 gender + \beta_4 ethnic + u$$

Each variable may contribute differently to the probability of departure, either increasing or decreasing, as shown in Figure 4.

Therefore, the *logit* model of the departure behavior represents the probability of outflow from the system, which becomes more complex when the causal effects take place. The departure model will be useful to the Brazilian Air Force manpower-planning sector to define the number of physician officers to recruit and to devise new retention policies.

Figure 4 Expected departure-behavior curve, log "S" shaped



2. System Dynamics

Ward (1994) comments that a well-designed model can help one understand the implications of the recent past, as well as the current environment for the future. It allows a good forecast to provide a comfortable lead-time to avoid or reduce the impact of unexpected situations or take advantage of future events.

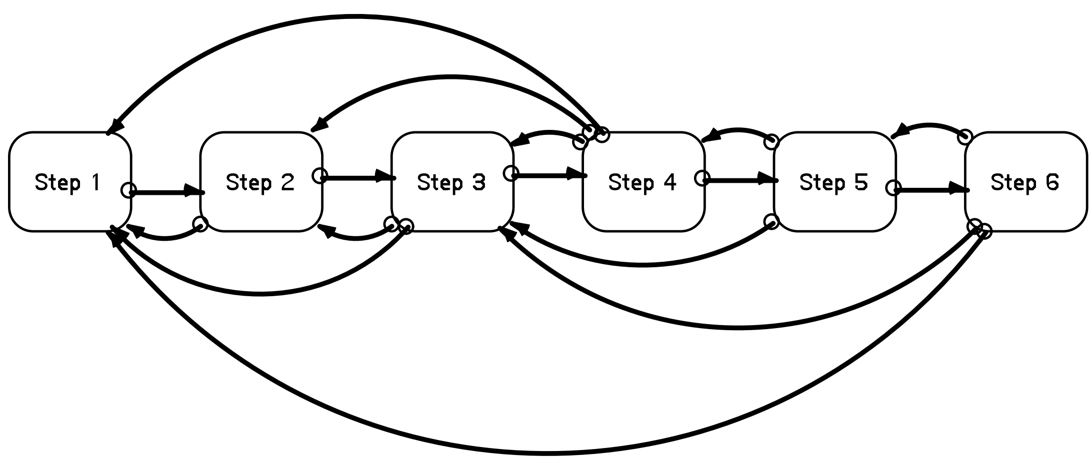
Tarek (1984) recalls Forrester and says that the behavior (or time history) of an organizational entity is mainly caused by its structure, including not only physical aspects, but policies and procedures that dominate the decision-making process.

The FABHS structure is affected by the flow of physicians, user demand, physician productivity, and delays that trigger decisions that will shape the system's behavior. Sterman (2000) comments that to find a solution to concerns related to the behavior of complex systems—where many disciplinary fields come together—one needs nonlinear models and feedback control that are related to mathematics, physics, and engineering. An interdisciplinary tool grounded in those fields is the key to enhanced learning in complex systems, and this is what system dynamics is all about. He recalls that, just as flight simulators help pilots learn to fly, system dynamics help decision makers learn about the complexity of system dynamics and how to design effective policies.

Senge (1990) makes the point that complex systems have feedbacks and delays, which lead to seeing organizations and social worlds in a more complete way. He notes that normally a decision is based on direct and obvious causes. Feedback enables systems to model problems better, and their solutions stem from the cumulative effect of previous decisions and actions—sometimes intentional, but often with hidden side effects. Sterman (2000) claims that the human mind, working without new technologies and methods, is unable to cognitively map and process the dynamic relationships within systems of complex causal relationships.

Forrester (1994) described a six-step system-dynamics process (Figure 5). The first three steps are within the scope of this research. Steps four to six deal with high-level policy decisions and will not be discussed in this work.

Figure 5 Forrester system-dynamics process



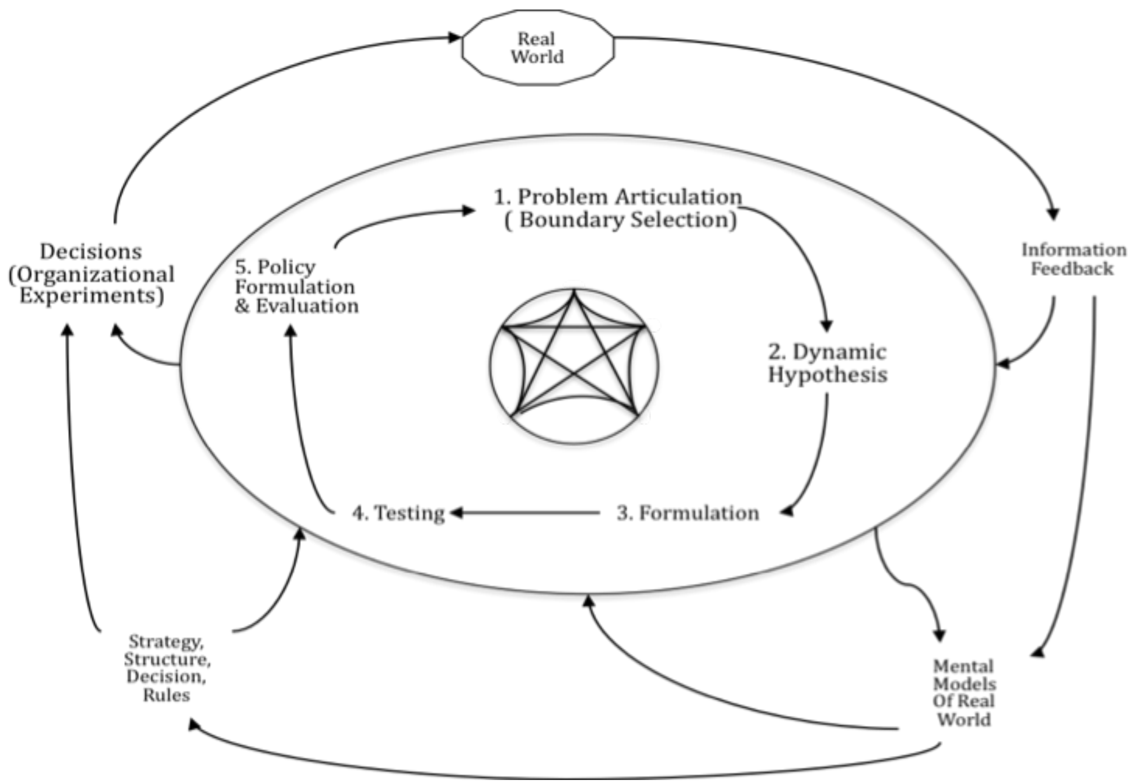
- Step 1: Describe the system
- Step 2: Convert the description to level and rate equations
- Step 3: Simulate the model
- Step 4: Design alternative policies and structures

- Step 5: Educate and debate
- Step 6: Implement changes in policies and structure

Ford (1999) improves Forrester's process and states the importance of starting the modeling process with a simple model and increasing complexity while development understanding of the system.

Sterman (2000) reinforces Ford's and Forrester's process by improving and reducing it to five essential steps that are representative of an iterative learning process (Figure 6). He comments about the necessity of systematic and continuous testing to build confidence in the model and gain insight into the system.

Figure 6 Modeling is an iterative learning process, from Sterman (2000)



Forrester (1994) recalls Forrester (1961) and Forrester and Senge (1980) in recognizing that there is no way to prove the validity of a theory that purports to represent behavior in the real world. He observes that there are no proofs for any of the laws of physics, only practical confidence that they are useful within bounds. Sterman (2000) declares that "all models are wrong," but they are useful for specific decision-making purposes; so the best model is the one available for the purpose at hand, despite its limitations. He recommends some tests (Table 4) for assessment of dynamic models, as shown below.

Table 4 Tests for assessment of dynamic models from Sterman (2000)

TEST	Purpose, tools and procedures
1. Boundary adequacy	Using causal- and feedback-loops diagrams to determine the boundaries of the model
2. Structure assessment	Looking for inconsistencies and indentifying the side effects of analyzing stock-and-flow maps and equations
3. Dimensional consistency	Specifying the units of measure for each variable and its consistency along the structure
4. Parameter assessment	Verifying the variables and constants that estimate the parameters
5. Extreme condition	Simulating and inspecting model equations using extreme conditions to determine robustness.
6. Integration error	Using different time steps to verify if the model results are sensitive to the choice of time step or integration method.
7. Behavior reproduction	Using the coefficient of determination, R^2 and other metrics such as mean absolute error (MAE) and mean absolute percent error (MAPE) to assess the model's ability to reproduce the behavior of a system
8. Behavior anomaly	Using loop-knockout analysis to reveal that some relationships must be included in the model when impossible or bizarre behaviors are generated
9. Family member	Asking whether the model can generate the behavior of other instances in the same class as the system the model was built to mimic
10. Surprise behavior	Verifying whether model behavior and model expectation have the same trend
11. Sensitivity analysis	Testing the robustness of conclusions when assumptions are varied over the plausible range of uncertainty
12. System improvement	Verifying if the modeling process can identify policies that lead to improvement

III. DATA SOURCE, MODEL DEVELOPMENT, PRELIMINARY DATA ANALYSIS

A. DATA SOURCE

The main data set used in the modeling process was obtained from the Brazilian Air Force personnel command (COMGEP) and encompasses officer-physician data from 1978 to August 2008.

The data provided detailed information such as name, rank, birth date, specialty, recruitment and exit dates, gender, and ethnicity. The data was entered in MS Excel and imported into *Stata 10 (2008)*, an integrated statistical-software package that provides tools for data analysis and management. The data was translated and grouped by cohort from 1978 and then into variables, to allow analysis and modeling as shown as in Table 5.

Table 5 Variables used in modeling

Variable name	Type	Comments
Departure	Categorical	One for those officers with an exit date, zero otherwise.
Experience	Numerical	Length of service from recruitment until July 31, 2008.
Age	Numerical	Physician age at exit date or at July 31, 2008.
Ethnicity	Categorical	One for white officers, zero otherwise.
Gender	Categorical	One for female officers, zero otherwise.

Table 6 summarizes the data received from the Brazilian Air Force. The number of observations represents the total physicians that entered the military from 1978 to 2008, and there is data for that specific variable.

Table 6 Data Summary

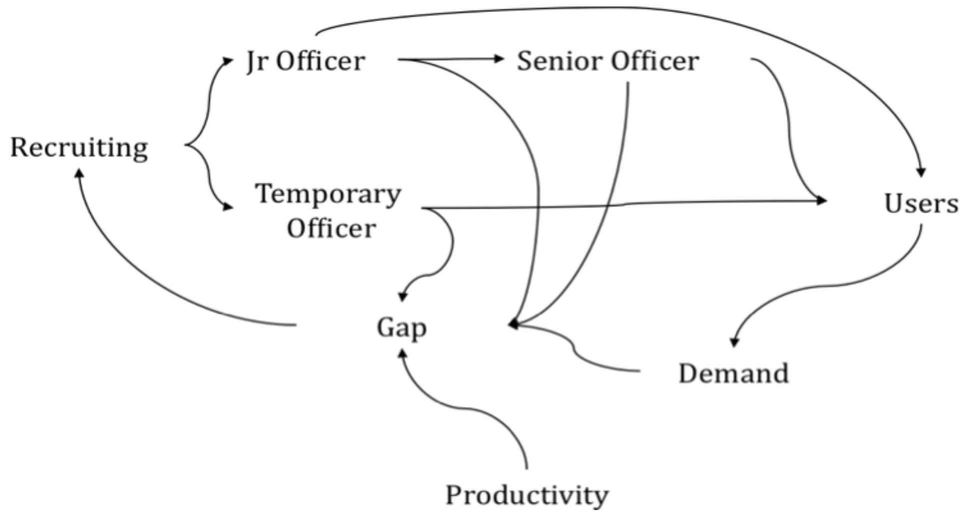
Variable	Obs	Mean	Std.Dev.	Min	Max
Saram	5226		CLASSIFIED		
exit_dt	3959	14718.71	2020.801	112	17749
retired	5226	.7571757	.4288308	0	1
active	5226	.2428243	.4288308	0	1
career	5226	.2566016	.4367994	0	1
gender	5226	.2152698	.4110487	0	1
ethnic	5226	.4001148	.4899683	0	1
enter_dt	5226	13411.23	3462.186	-1613	17650
age (exit_dt)	5226	32.86896	7.920149	21.66849	67.09315
agesq	5226	1143.085	604.6899	469.5236	4501.49
departure	5226	.7575584	.428601	0	1
exper (days)	5226	2040.931	2679.154	6	14762
Experyr (yrs)	5226	5.591593	7.340147	.0164384	40.44384
expyrsq	5226	85.13336	190.6815	.0002702	1635.704
aexp	5226	237.1213	380.1993	0	2591

Saram is the individual code that is used to identify each person; for privacy reasons it is classified information. The categorical variables, such as retired, career, and departure, received a value of 1 when the event named by the variable occurred, and 0 otherwise. The variable gender is 1 when a physician is female, and 0 otherwise. The variable *ethnic* is 1 when information was given as white, and 0 otherwise. Dates in *Stata* are integer numbers, where the value records the number of days that have passed from an agreed-upon base, which is 1/1/1960; so in the data the negative number represents dates before base value. The same convention is used for entrance and exit dates.

B. MODEL DEVELOPMENT

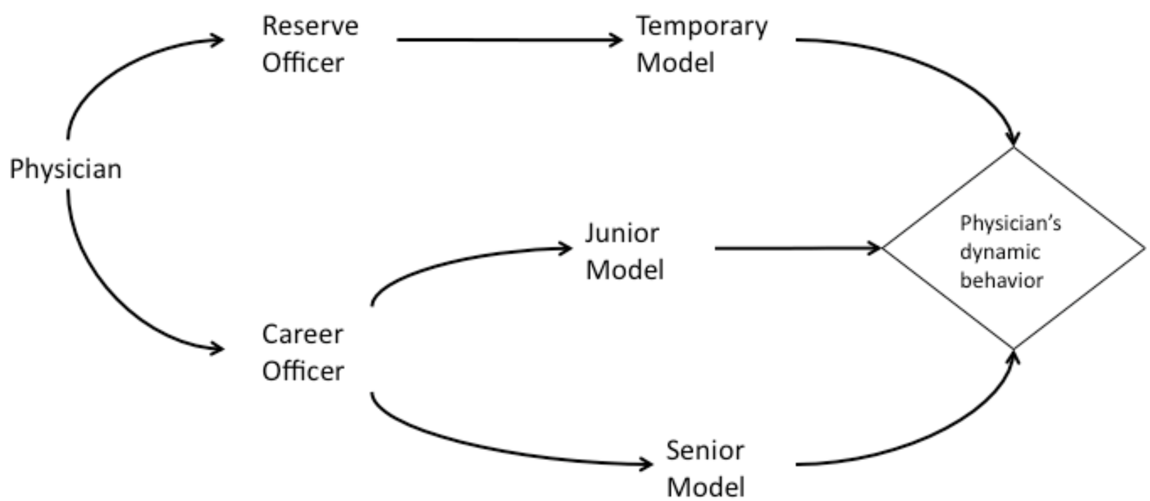
Following steps one through three of the modeling process developed by Sterman (Figure 6), and focusing on parts of the model that by themselves encompass an individual complex model, this section will follow the diagram shown at Figure 7 to develop the knowledge and understanding needed to explore physician-manpower policies for the Brazilian Air Force.

Figure 7 Diagram for modeling demand for physicians



To build a dynamic-behavior model, the data was split into three groups, with behaviors differing over the timeframe according to the variables that drive them. These are different for each, as shown in Figure 8.

Figure 8 Model of simplified framework



1. Problem Articulation

a. Junior Officers

The source of physicians who become career officers is a national selection exam that occurs once a year. The number recruited annually is a function of the need for physicians, desired ratio between career and temporary officers, and the physical limitations of teaching facilities, which for career officers is located in downtown Belo Horizonte, Brazil.

After graduation, a junior-officer physician begins his career as a first lieutenant and is eventually promoted to captain. Promotion to senior officer normally takes fifteen years, but promotion polices are subject to change. Promotion policies are intended to function by establishing flow and keeping the desired quantities in each rank group.

During the period analyzed (1978–2008), the promotion policies governing junior career officers changed, sometimes affecting retention. Although promotion policy changes occurred a few times in the past, they do not represent the normal behavior of departure.

Initially, the data was analyzed in *Stata* using the following model to obtain the junior-officers' dynamic departure behavior:

$$\text{logit}\left[\hat{\pi}(departure)\right] = \beta_0 + \beta_1 age + \beta_2 experience + \beta_3 gender + \beta_4 ethnic + u$$

The model for junior officer departure should also include one additional variable (age^2) to reflect external-market activity that affects physician departures, due to increasing job opportunities for younger officers. To reflect this behavior, a quadratic function was needed. Additionally, the variable *experience* is not statistically significant for predicting junior-officer departure. This result is justified by the fact that a junior officer has little experience as a military physician to encourage him to depart in favor of outside-market opportunities, as compared with the career opportunities available to a senior officer. So, this variable was dropped for the junior model.

Table 7 Junior multivariate model based in *logit* regression

Departure	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
age	-.8003735	.2571203	-3.11	0.002	-1.30432	-.296427
age^2	.0102282	.0034622	2.95	0.003	.0034424	.017014
gender	-1.637759	.2470088	-6.63	0.000	-2.121887	-1.153631
ethnic	-2.595064	.2076216	-12.50	0.000	-3.001995	-2.188134
_cons	16.5407	4.720814	3.50	0.000	7.288071	25.79332

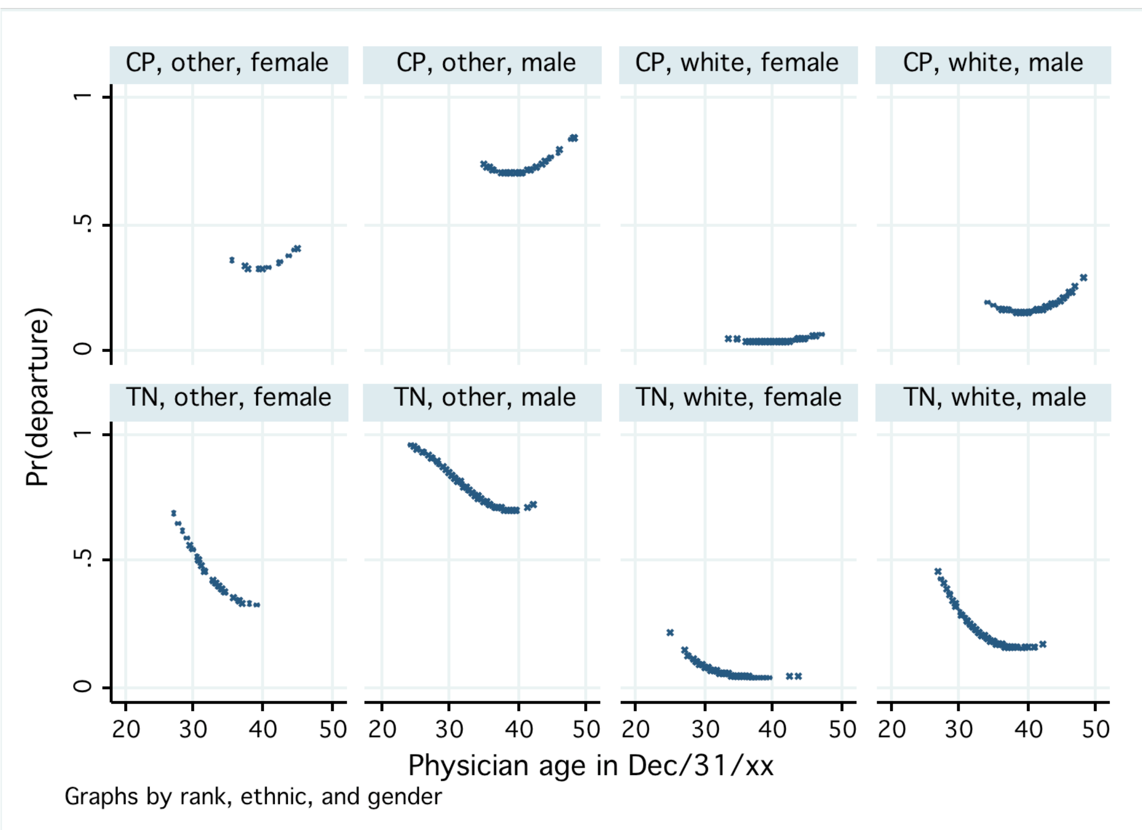
Thus, using the multivariate *logit* regression results (Table 7) the model that reflects the dynamic departure behavior for junior physicians during the period 1978 to 2008 can be expressed as,

$$\operatorname{logit}\left[\pi\left(departure\right)\right]=16.54-.8age+.01age^{2}-1.64gender-2.6ethnic$$

The output of the multivariate model is graphically represented in Figure 9. It can be observed that the probability of departure behavior for each variable group is different.

The number of junior officers recruited each year must compensate for the dynamic, complex departure behavior of the overall career-physician stock, so variables such as age, experience, gender, and ethnicity need to be analyzed and compared to get the closest predicted value for the junior-officer departure-behavior ratio.

Figure 9 Departure behavior of junior-officer physicians: *Stata* output



b. Senior Officers

The senior officer pool receives inputs from the junior officer pool every time a medical captain is promoted to a medical major. The senior-officer departure-behavior ratio reduces the overall stock of physicians. This behavior is summarized as a multivariate-regression output in Table 8. The senior officer dynamic departure behavior during the period 1978 to 2008 can be expressed as,

$$\text{logit}\left[\pi\left(departure\right)\right] = 9.6 - .424age + .005age^2 + .074exp - 1.7gender - 2.66ethnic$$

Figure 10, 11 and 12 represent the output of the multivariate regression model according to the officer's rank, i.e., major, lieutenant colonel, or colonel. To account for the wide range of output caused by years of experience, the departure probability behavior was graphed in the first year of each rank. Here it can be observed that gender difference has a low influence on the probability of departure behavior, because the actual female physician senior officers are all majors, because only recently the Brazilian Air Force started admitting female physicians.

Table 8 Senior multivariate model based in *logit* regression

departure	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.4238432	.1068045	-3.97	0.000	-.633176	-.2145103
exp	.0739828	.0260109	2.84	0.004	.0230023	.1249633
age^2	.0049884	.0012496	3.99	0.000	.0025392	.0074376
gender	-1.692641	.2353982	-7.19	0.000	-2.154013	-1.231269
ethnic	-2.65759	.1613757	-16.47	0.000	-2.973881	-2.341299
_cons	9.584292	2.243985	4.27	0.000	5.186163	13.98242

c. Temporary Officers

The number of temporary officers as well as their departure behavior affects the overall stock of physicians. Temporary officers have a psychological factor behind their departures; their contract indicates that and after eight years they must leave the military. Any small market opportunity can drive their decision to leave and, for the scope of this research, this kind of opportunity is not displayed in the departure models, which predict their departure behavior with the discussed variables. The temporary-officer multivariate regression is summarized in Table 9.

Figure 10 Departure behavior for senior-officer physicians. Rank: major with eighteen years of military experience.

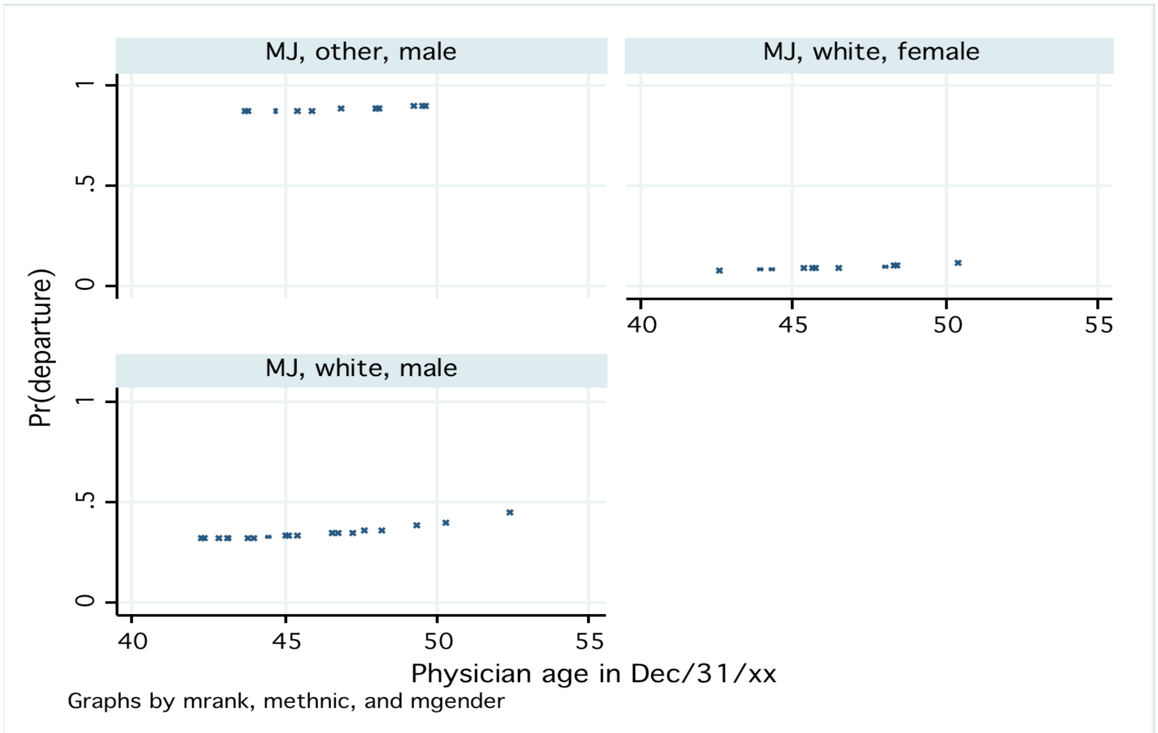


Table 9 Temporary-officer physician multivariate model based in *logit* regression

departure	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.1025275	.016445	-6.23	0.000	-.1347591	-.0702958
exp	.4269869	.0333863	12.79	0.000	.361551	.4924228
ethnic	-1.63817	.1009885	-16.22	0.000	-1.836104	-1.440236
gender	-.9745433	.1091207	-8.93	0.000	-1.188416	-.7606706
_cons	4.974431	.4545514	10.94	0.000	4.083526	5.865335

The departure-behavior model for temporary physicians during the period 1978 to 2008 can be expressed as:

$$\text{logit}\left[\pi\left(departure\right)\right] = 4.97 - .102age + .427exp - .97gender - 1.64ethnic$$

The three departure-behavior models shown above provide a more accurate dynamic-outflow rate than a simple ratio. There are other factors that affect the outflow, but the variables in these models are sufficient to define one of the boundaries of this research.

Figure 11 Departure behavior for senior-officer physicians. Rank: lieutenant colonel with twenty-two years of military experience.

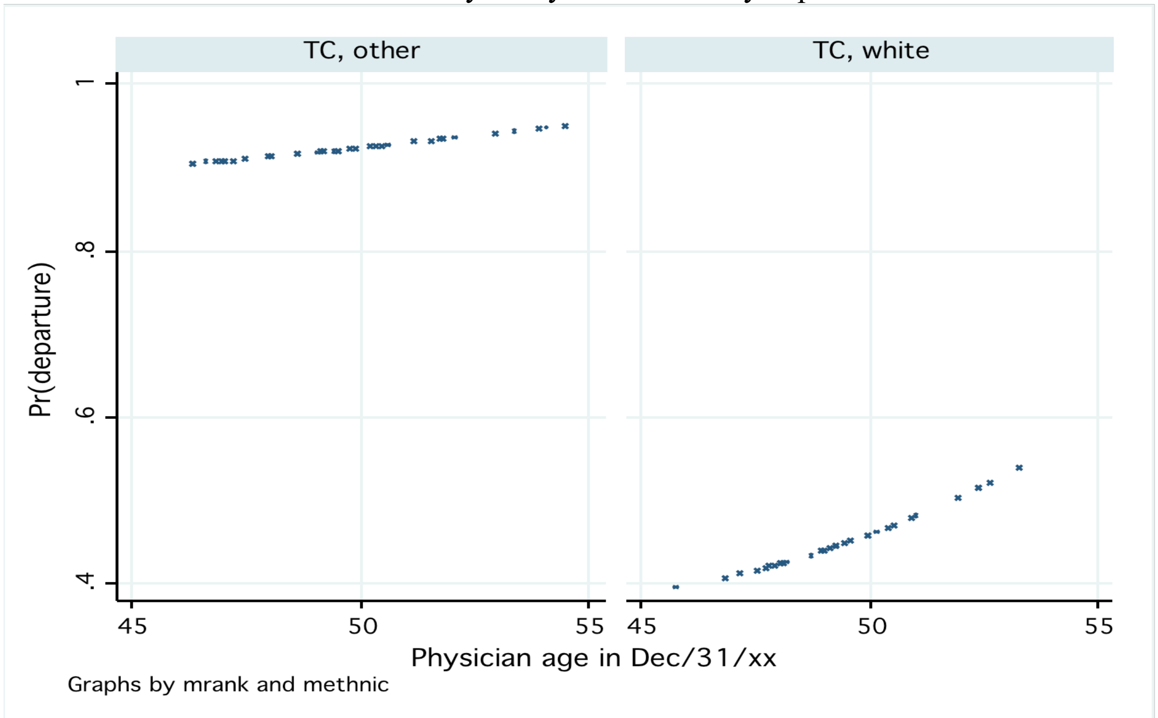
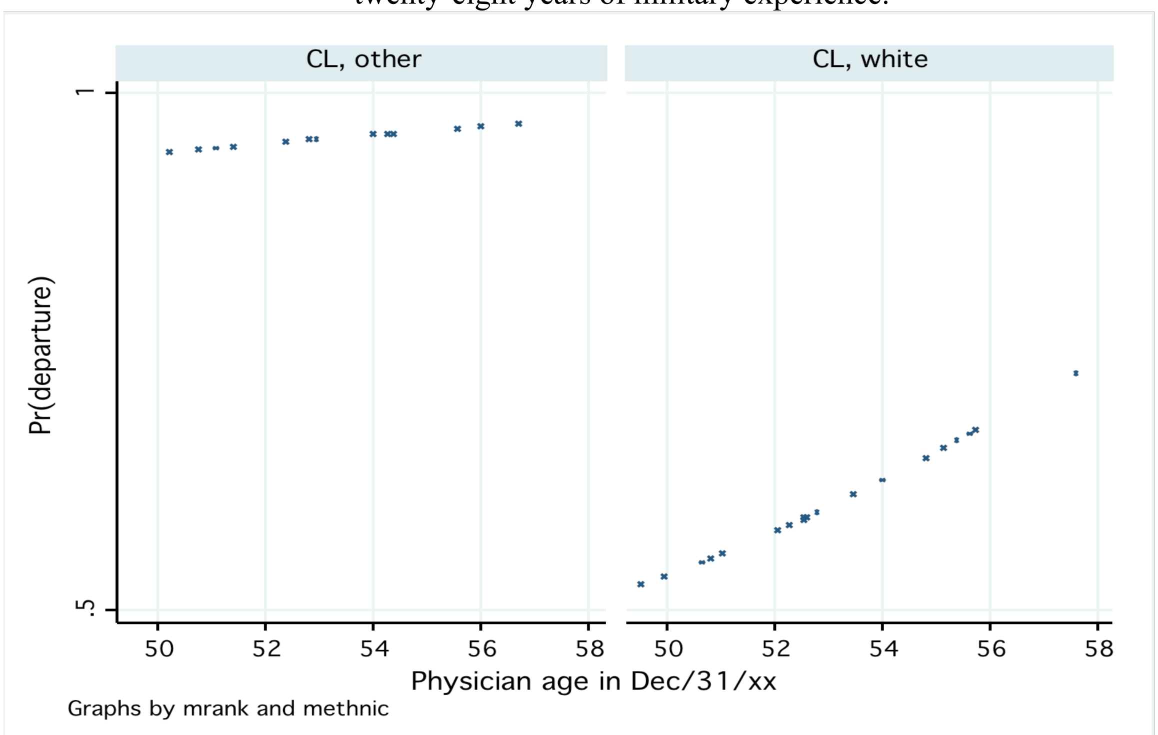
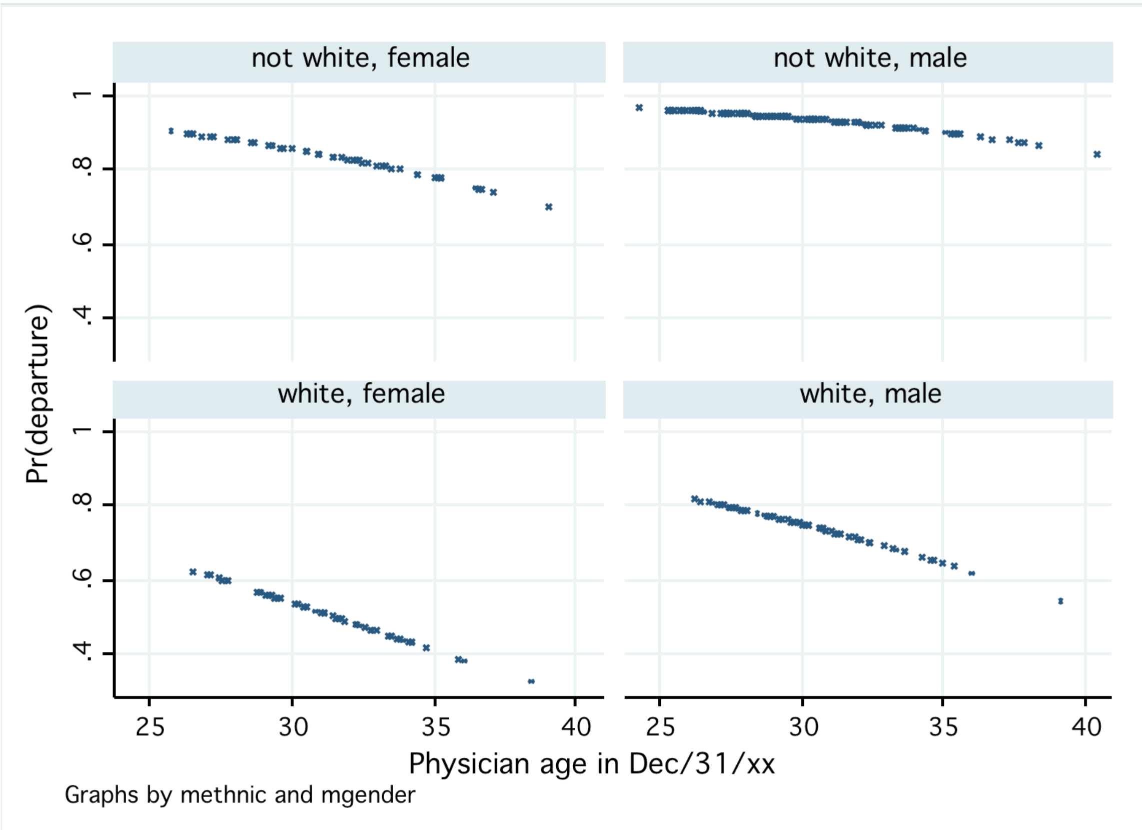


Figure 12 Departure behavior for senior-officer physicians. Rank: colonel with twenty-eight years of military experience.



Contracting the sum of quantity that departure showed could keep the physician stock at a steady level, balancing outflow and inflow, but the service level would deteriorate over time through changes in other variables affecting the dynamic system. Thus, the number of users and the demand for physicians must be estimated and simulated.

Figure 13 Departure behavior for temporary-officer physicians with two years of military experience.



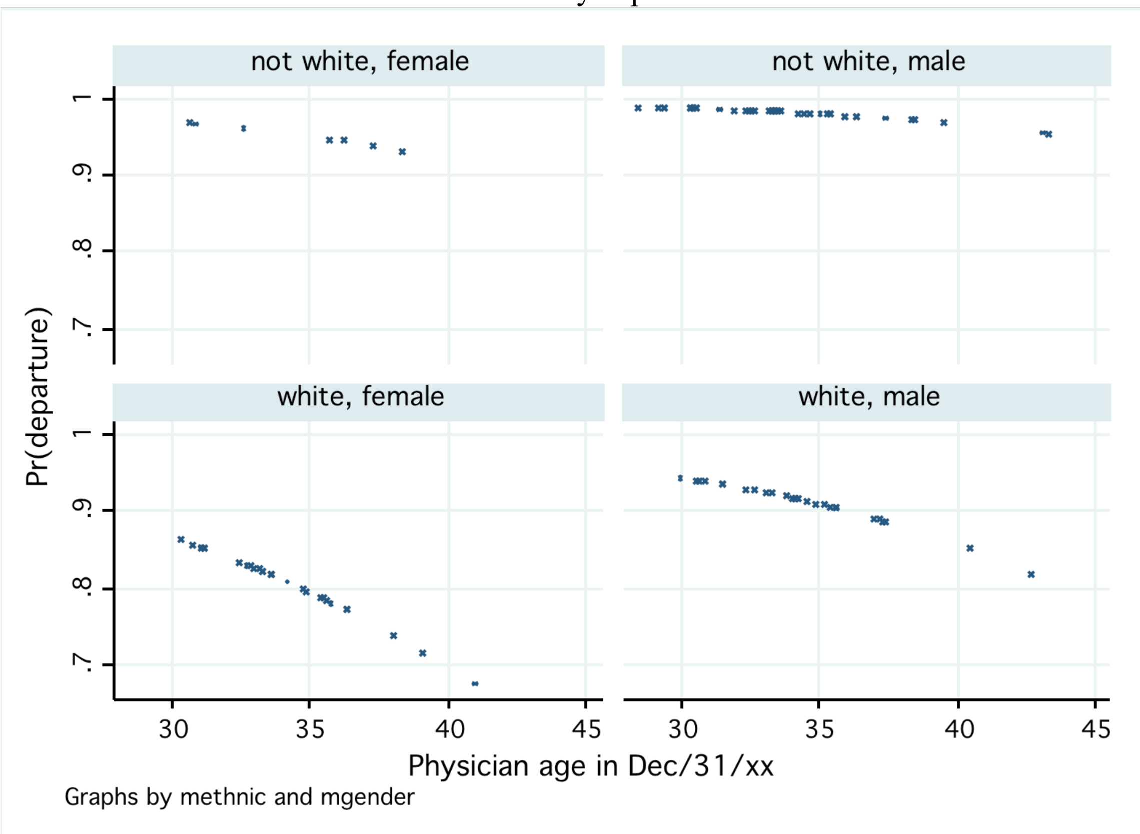
d. Users

The number of users is represented by the following formula:

$$users = total\_military + total\_retired + dependents$$

The total military variable represents the total Brazilian Air Force stock, which, as the physician stock, is modified by inflows and outflows. To keep this research unclassified, the military total used in the model is 90% of the maximum allowed by the law. For the purposes of simulation, the start scenario permits a 10% increase in total military stock. Another assumption for this military model is that inflow and outflow is balanced, i.e., the system is in a steady state, allowing for changes in military-physician inflow and outflow according to the law.

Figure 14 Departure behavior for temporary-officer physicians with six years of military experience.



The total number of officers is limited by law, so the stock of physicians can grow only to the limit defined for officers overall. The assumption is made that if the upper limit is reached and the number of physicians needed increases to meet the maximum number, other officer communities need to lower their inflow so as not to exceed the legal limit.

Service time is another variable that affects total military stock. We assume that the duration of active military duty is thirty years. After that, an officer leaves the military and becomes an inflow into the retired stock. The retired-stock outflow is based on the average life expectancy of a Brazilian citizen, which is sixty-eight years old, according to the Brazilian Institute of Geography and Statistics (IBGE - 2000).

The following assumptions are used as standard to simulation in this research: first, the number of years that someone uses the health system as a retired is based on the following formula:

$$retired\_time = life\_expec - (recruit\_age + 30\, years),$$

where *life_expec* is the average life expectancy and *recruit_age* is the average recruitment age for the overall military community (the Brazilian data shows that it is nineteen years old).

The second assumption is that both groups, military and retired, have the same average number of dependents, calculated as,

$$dependents = (total\_military + total\_retired)dep\_ratio,$$

where dep_ratio is the average number of dependents, per military or retired.

e. Need for Physician

The "need for physicians" represents a theoretical value defined as,

$$needs = \frac{user\_demand}{physician\_productivity},$$

where *user_demand* is the average number of visits per year (a function of the number of users) and *physician_productivity* is the average number of visits that a physician can conduct per year. Thus the result is the number of physicians needed during the year.

The user-demand formula is,

$$user\_demand = users * \frac{visits}{user / year},$$

where the average visits per user per year is a desired ratio that represents usage of the health system. For an initial scenario, this variable was set equal to the average value estimated by COMGEP, two visits per user year. Thus the demand for visits per year is equal to twice the number of users.

Physician productivity, for the scope of this research, is based on the following formula:

$$productivity = workday * visitshour * daysworked ,$$

where *workday* is the average number of hours worked by a military physician per day, *visitshour* is the average number of visits that a military physician can conduct in one hour and *daysworked* is the average number of days effectively worked in visits by a military physician.

2. Dynamic Hypothesis

Sterman (2000) comments that, after indentifying a problem and characterizing it over a time horizon, the next step is to focus on developing a theory, or a dynamic hypothesis. He observes that a hypothesis is always provisional, subject to revision or abandonment as more knowledge is gained from modeling and from the real world.

To develop knowledge and explore models, as well as to perform simulations, *Stella 9.1* (Isee Systems, 2009) was used to provide the flexibility of a graphically oriented approach and the ability to develop proper equation structures.

To understand the feedback and physical structure of physician behavior, this research has developed causal-loop diagrams and stock-flow maps for each of the main groups, as cited in Figure 8.

a. Junior Officers

The junior-officer physician diagram (Figure 15) shows that changes in the recruit rate affect the junior-officer population. The positive link means that if causes change, the effect changes above or below what it would otherwise have been in the same direction of the cause. So, for example, an increase in the recruit rate results in an increase in the junior-physician population and more junior physicians leads to more promotions and departures. A negative link means that if the cause changes, the effect changes above or below what it would otherwise have been in the opposite direction of the cause. Thus, higher junior-officer promotion rates and departure rates reduce the junior-officer population.

Sterman (2000) says that link polarities describe the structure of the system. He explains that they do not describe the behavior of variables, but they describe what would happen if there were a change. He comments that the negative link indicates a subtraction from the effect, i.e., a drop in the junior departure rate does not add to the junior population. It means that fewer junior physicians are leaving the system and more remain as military.

The loops in Figure 15 are negative loops or balancing loops **(B)** that lead the system to a steady state; in this case, the goal is to equilibrate promotion and departure rate with the recruit rate. Sterman (2000) comments that all negative loops have goals.

Causal loops are good tools for capturing feedback behavior, but they are limited to capturing the stock-and-flow structure of the system. Sterman affirms that stocks and flows, along with feedback, are the two central concepts of dynamic-system theory.

Figure 16 shows stock and flow for junior physicians. Sterman (2000) recalls Forrester, 1961 and says that stock-and-flow diagramming conventions are based on a hydraulic metaphor, i.e., stocks are like a bathtub of water, and the quantity of water in the bathtub at any time is the accumulation of water flowing in through the tap less water flowing out through the drain.

Figure 15 Junior-officer diagram

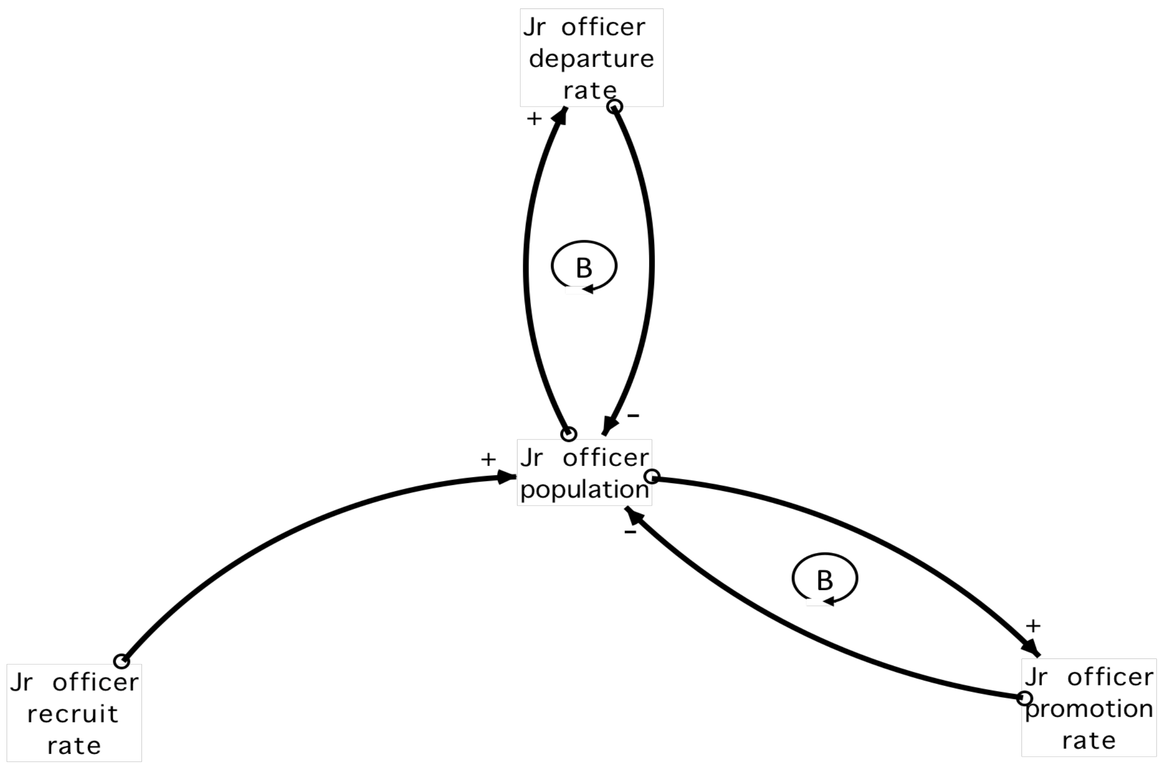
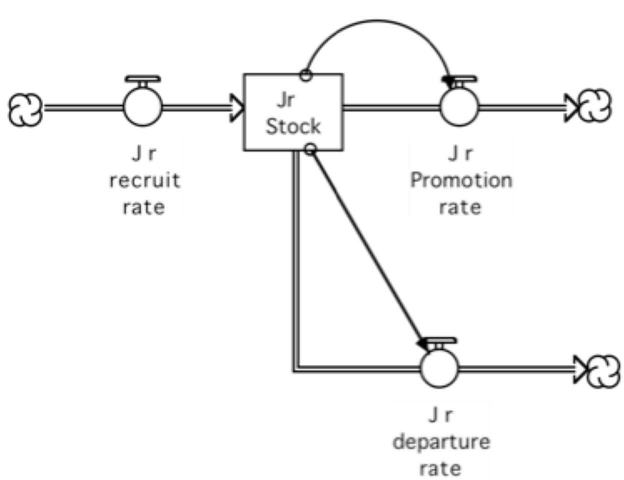


Figure 16 Junior-officer stock-and-flow diagram



Hence this structure can be represented as the following equation:

$Stock(t) = \int_{t_0}^{t} [recruit - (promotion + departure)]\,ds + Stock(t_0)$, i.e., the stock at the current time t is the integral of the difference between the inflow (recruitments) and the outflow (sum of promotion and departure) at any time *s* between the initial time t_0 and the current time t plus the initial stock.

The recruitment rate is a function that drives the recruitment quantity, which is a part of this research's goal, and is presented in the next chapter, model results. The promotion rate is based on time, i.e., years in the junior ranks. The junior departure rate was discussed in the previous section and it is based on a multivariate-regression model.

The dynamic model for junior-officer physicians, with all variables used in this research, is represented in Figure 17. The new structure-added functions accrue the behavior of the variables that are in the multivariate departure behavior rate. Sterman (2000) calls this new structure added *coflows* and says it is needed when the outflow rates of items from a stock depend strongly on the age of the items. The departure model and promotions depend greatly on age.

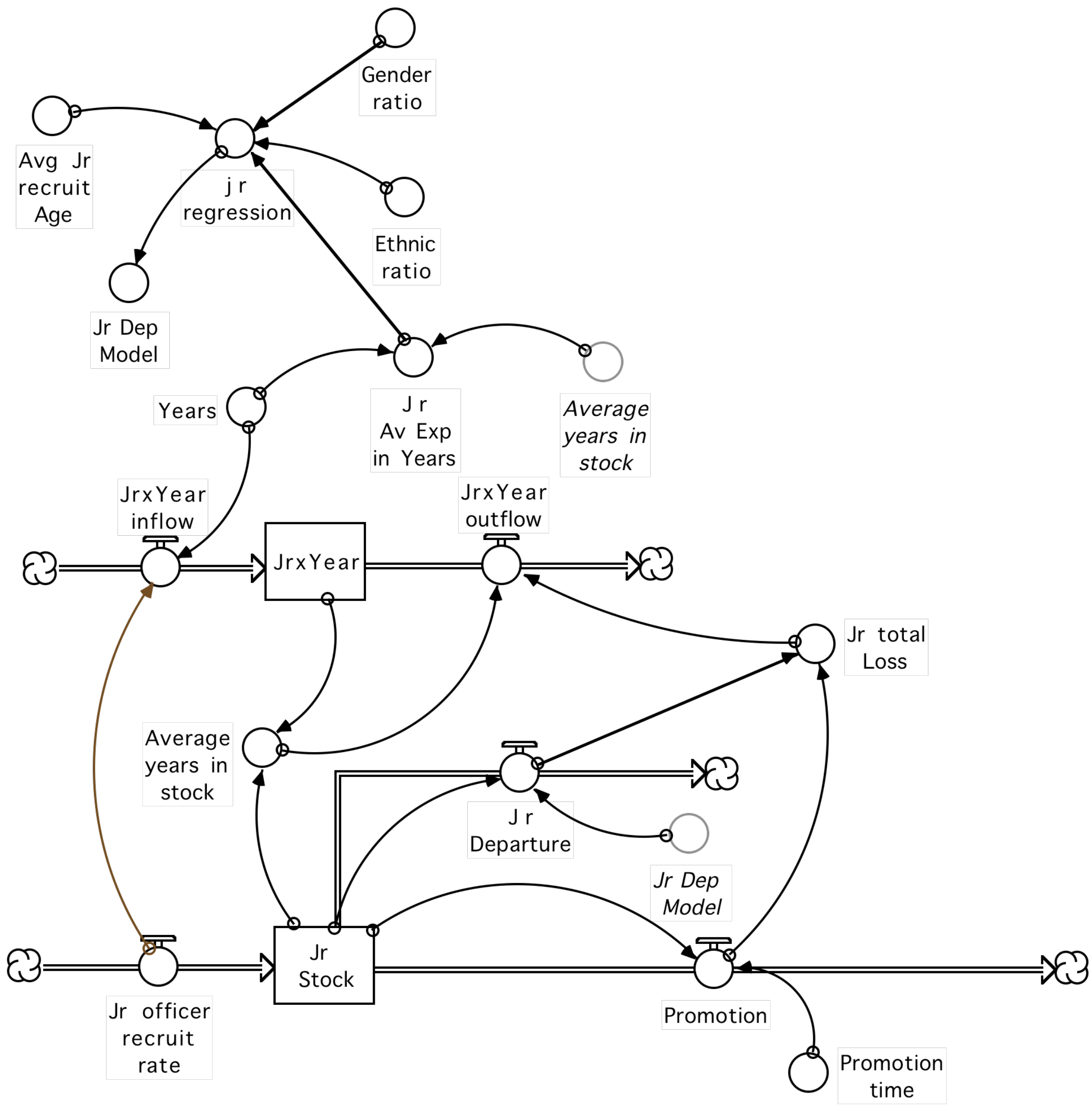
The diagram in Figure 17 uses the coefficients obtained with the multivariate regression shown in Table 6, as follows. The variable named in Figure 17 as "*Jr Av Exp in Years"* is the experience calculated using the recruitment year and the length of time in stock. This variable is not used directly in the model, as explained earlier, because it is not significant for junior-departure behavior, but rather, it is the aging of the physicians in stock when used together with the recruit age.

To verify and simulate different scenarios in the system dynamics model, the variable *Avg Jr recruit Age* (the average age of a cohort at recruitment) added to the *Jr Av Exp in Years* results in the actual age, which is used in the junior regression (in the model above) with the variable *Gender ratio* (gender distribution of a cohort) and the variable *Ethnic ratio* (ethnic distribution of a cohort) to predict the probability of departure. The *Jr Dep Model* is a dynamic parameter derived from this multivariate regression:

$$\pi\left(departure\right) = \frac{exp(\beta_0 + \beta_1 age + \ldots + \beta_4 ethnic)}{1 + exp(\beta_0 + \beta_1 age + \ldots + \beta_4 ethnic)},$$

where the parameters β are the coefficients in Table 7. This formula is used to calculate the *departure ratio*, as explained in Chapter II.

Figure 17 Junior-officer physician stock-and-flow-structure diagram



Jr Departure is the result of the multiplication of *Jr Stock* and the *departure ratio*.

Promotion contributes to the overall outflow from *Jr Stock* and is the inflow for the senior-physician model. This variable, added to *Jr Departure,* yields *Jr total loss,* which is the overall attrition that occurs in the junior-physician population.

b. Career Officers: Junior and Senior

The career-officer-physician diagram in Figure 18 shows the junior-officer feedback diagram coupled with the senior-officer diagram. Changes in the promotion rate lead to changes in the senior-officer population in the opposite direction as the changes in the senior-officer departure rate. This new negative loop balances the promotion rate (inflow) with the departure rate (outflow).

The career-officer physician stock-and-flow-structure diagram in Figure 19 couples the junior-officer physician stock-and-flow diagram (Figure 17) with the senior-officer model.

Figure 18 Career-officer diagram

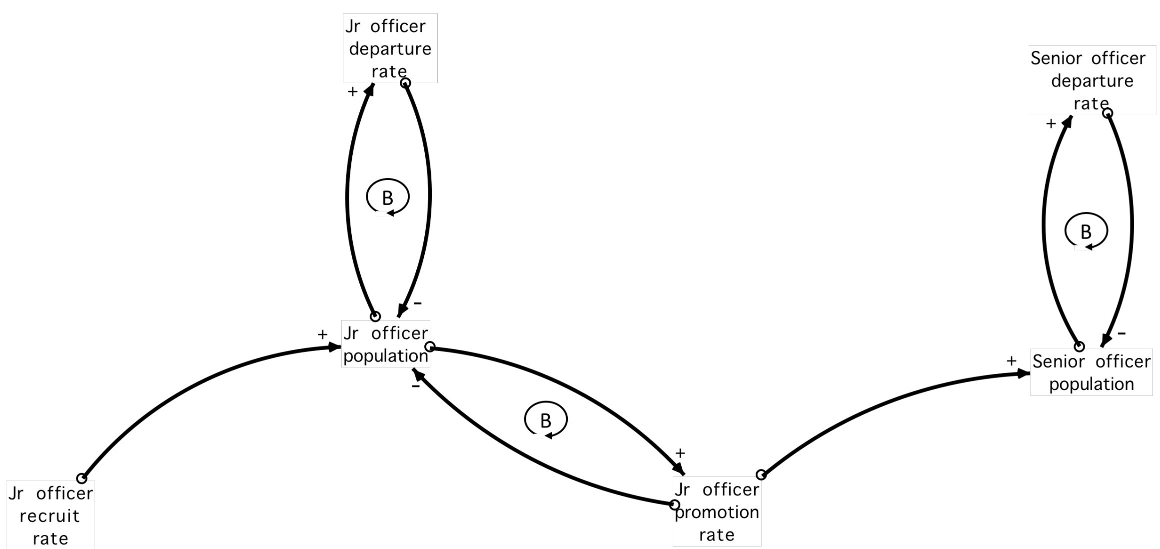
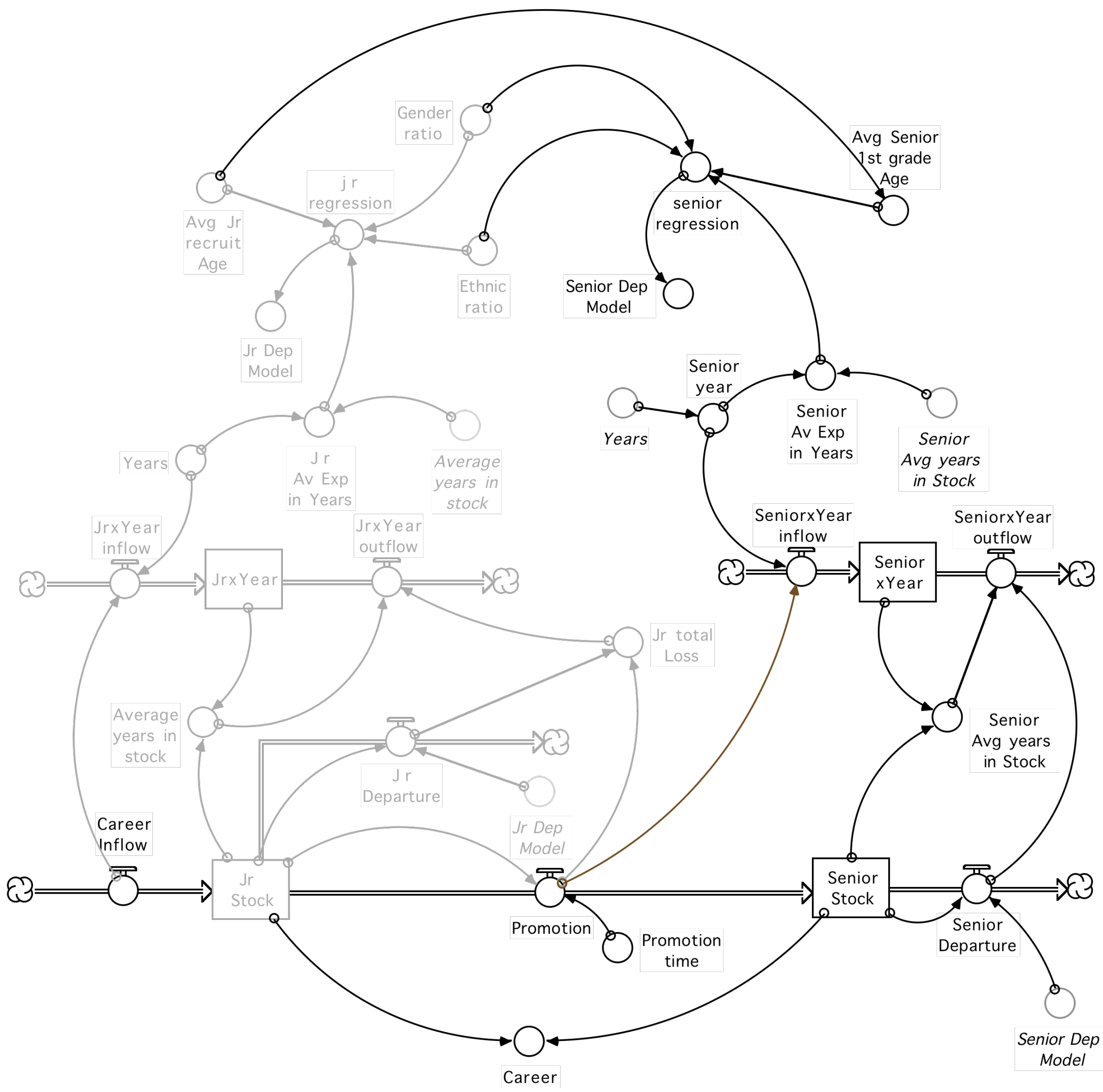


Figure 19 Career-officer physician stock-and-flow-structure diagram, senior officers highlighted



Initially, the *Jr officer recruit rate* (Figure 17) has the variable name changed to *Career Inflow* (Figure 19) so as to get an overall career-model visualization. Similarity as *Jr regression*, *Senior regression* keeps gender and ethnic distribution and has age transformation based on length of experience to calculate the initial senior age or the *Avg Senior 1st grade Age*. The *Senior regression* in the diagram above has coefficients as shown in Table 8.

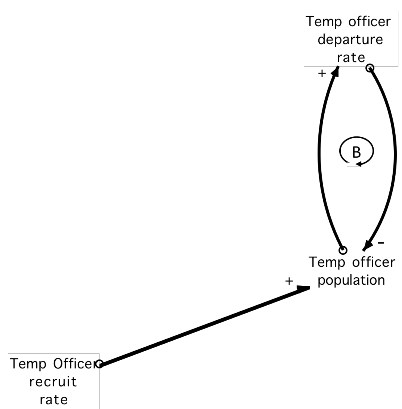
The *Senior Dep Model* (senior-departure model) is based on Table 8 coefficients and when multiplied by *Senior Stock* results in the predicted departure figure for each year.

The career-officer stock-and-flow model shows physician behavior over time and contributes to predicting overall military-physician departure, which is needed to complete the temporary-officer behavior over time.

c. Temporary Officers

The feedback structure for temporary officers is similar to that of senior officer, if there is only one outflow in the departure rate (Figure 20). The goal is to balance the departure rate with the recruit rate.

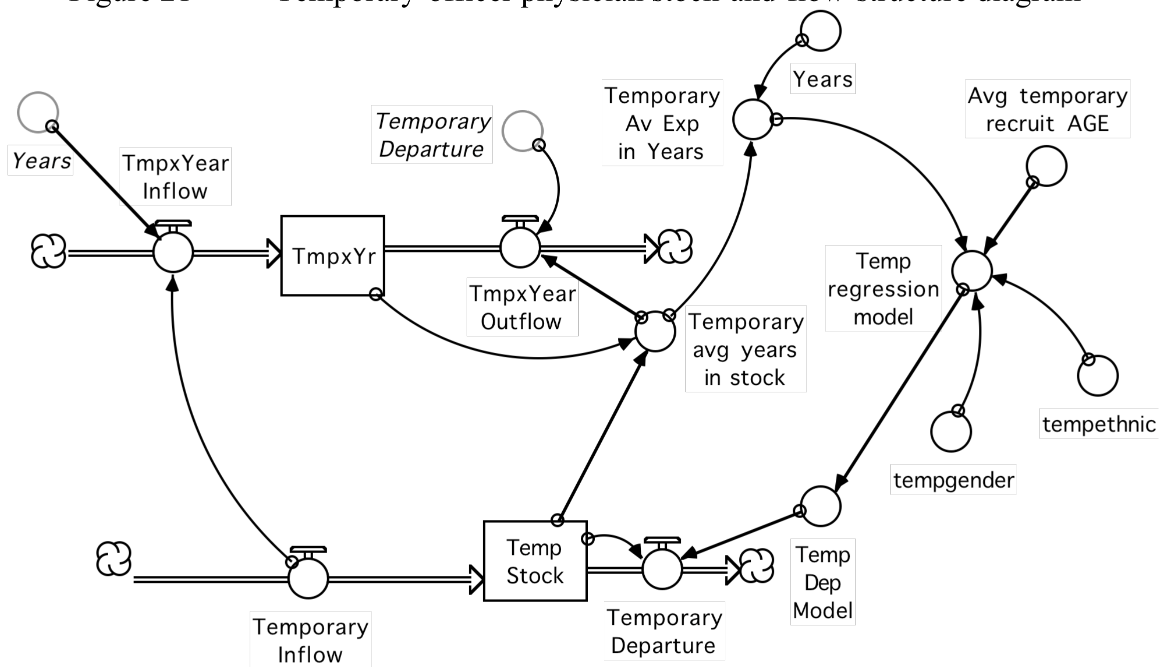
Figure 20 Temporary-officer diagram



The stock-and-flow diagram for temporary-officer physicians (Figure 21) has the same basic structure as for career officers with the difference in the multivariate model, which for temporary-officer physicians is the model described in Table 9. The temporary model uses a different set of physician characteristics (age, experience, gender, and ethnicity) for the temporary-physician population because it is not equal to that of career physician.

With the stock-and-flow-structure models above it is possible to simulate and predict overall physician behavior over time, as well as physician stock and total departure. Additionally, overall physician stock is a part of user stock.

Figure 21 Temporary-officer physician stock-and-flow-structure diagram

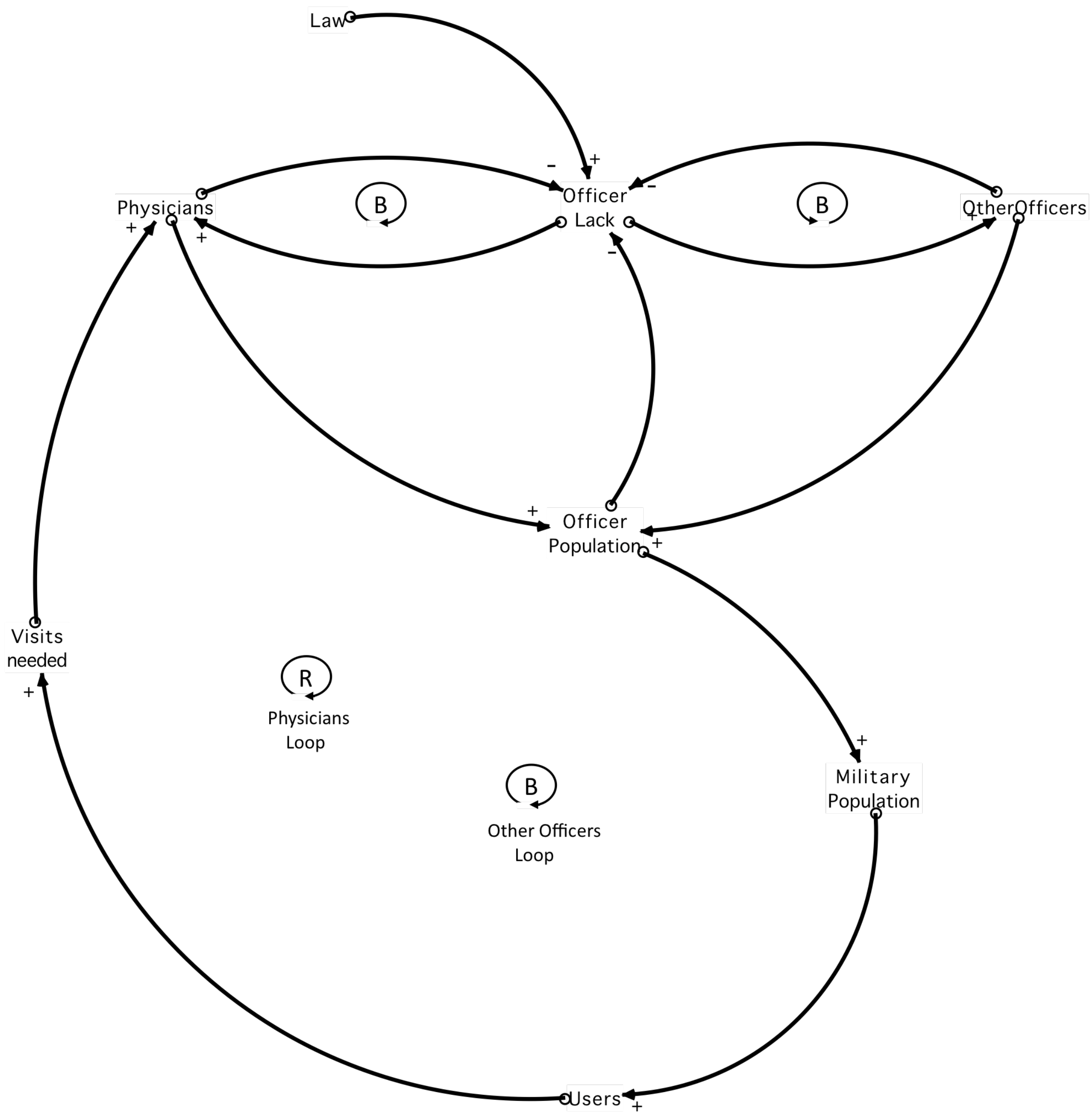


d. Users

Users, as explained above, are the total sum of active military, retired, and dependents. In the User Diagram (Figure 22), the variable *Law* defines the maximum number of officers and overall personnel. This constraint, and the assumption that there are fewer officers than authorized, results in an *Officer lack*, which drives *Physicians* and the *Other officers* community towards recruiting. Both population loops, *Physicians* and *Other officers*, are balancing loops or negative, and the goal is to balance *Officer Population* with *Law* limitations.

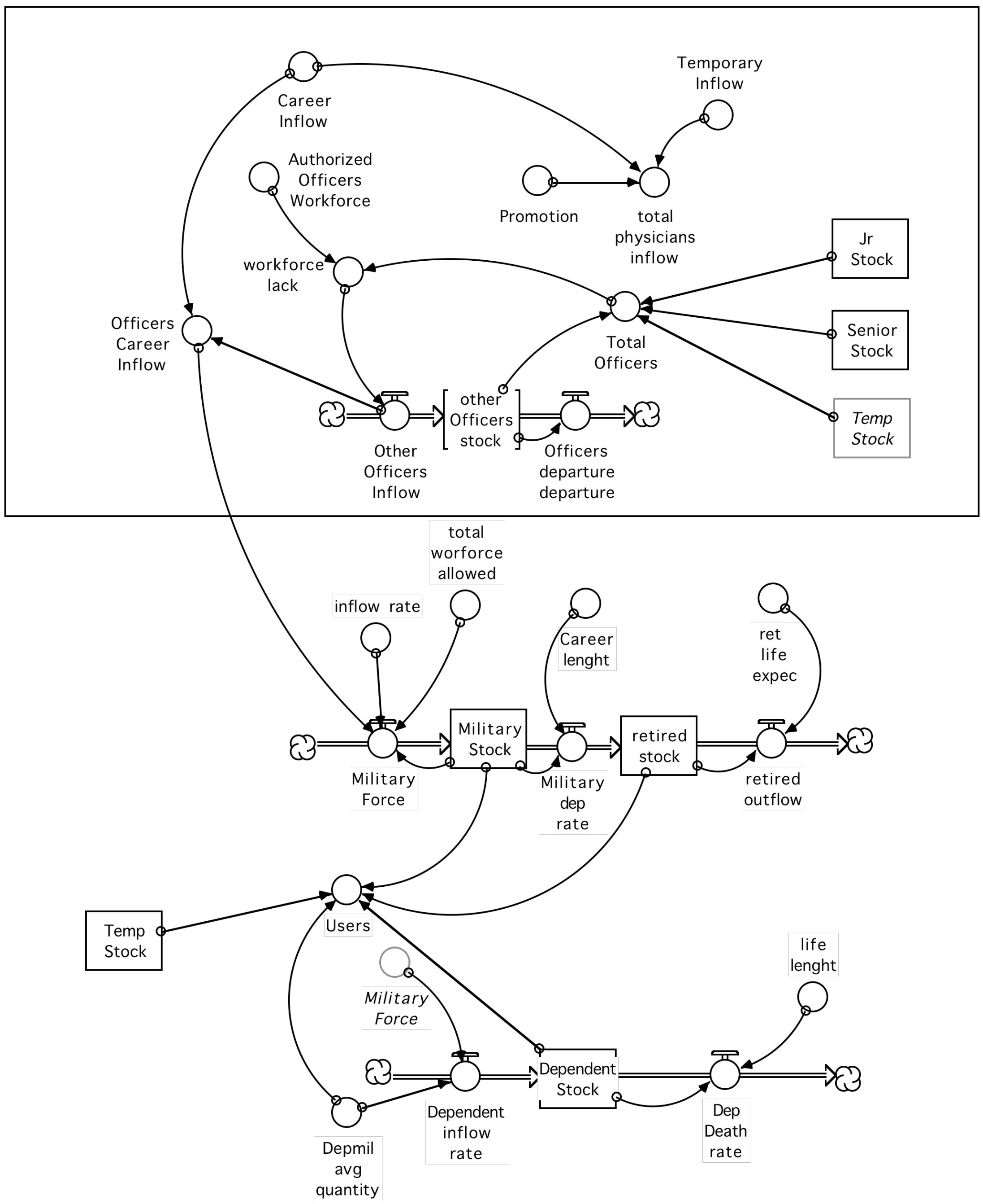
Physicians Loop is a reinforcing loop, i.e., there is a tendency to keep the same trend over time, increasing or decreasing in function of the change in the *Physicians* population. On the other hand, *Other Officers Loop* is a negative loop that looks for a balance between the *Officer Population* and the limits of the *Law*. Here, another assumption is made: the focus is on the number of physicians, *Other officers* is driven by the number of physicians and the legal limits, i.e. every time the simulation reaches the legal officer limit, there will be a reduction in *Other officers* recruitment to allow space for increasing physicians, if needed.

Figure 22 User Diagram



The stock-and-flow diagram for users is a little more complex than for physicians, since the user model needs to encompass part of the models above and of other factors that defining users quantity. Figure 23 is a preliminary model for predicting the number of users. Future research must be done to predict more precisely the whole military, retired, and dependent population's behavior over time.

Figure 23 User stock-and-flow-structure diagram



The first group of stock and flow (inside the square) is the *other Officers* stock and flow, and it is the simplest model for deriving behavior over time, where the inflow is the lack of *workforce*, i.e. the space that exists for growth. The *other Officers Inflow* is the physician *Career Inflow* and the overall *Officers Career Inflow*. The same law that limits officer quantity defines the *total military workforce allowed,* which constrains the *Military Force* inflow. Here is the second part of the *User Stock and Flow* model, where the total military is predicted and together with the number of *Dependent Stock* and *Temporary Officer Stock* becomes the number of *Users*. The *temporary Officer Stock* allows the calculation of temporary-officer dependents, which stay in the system while the temporary military is part of the system.

The average number of visits that a user needs per year defines the average demand per physician while a physician can complete a certain number of visits per day. Thus, in the next section the preliminary dynamic quantity of physicians needed by the Brazilian Air Force health system is defined.

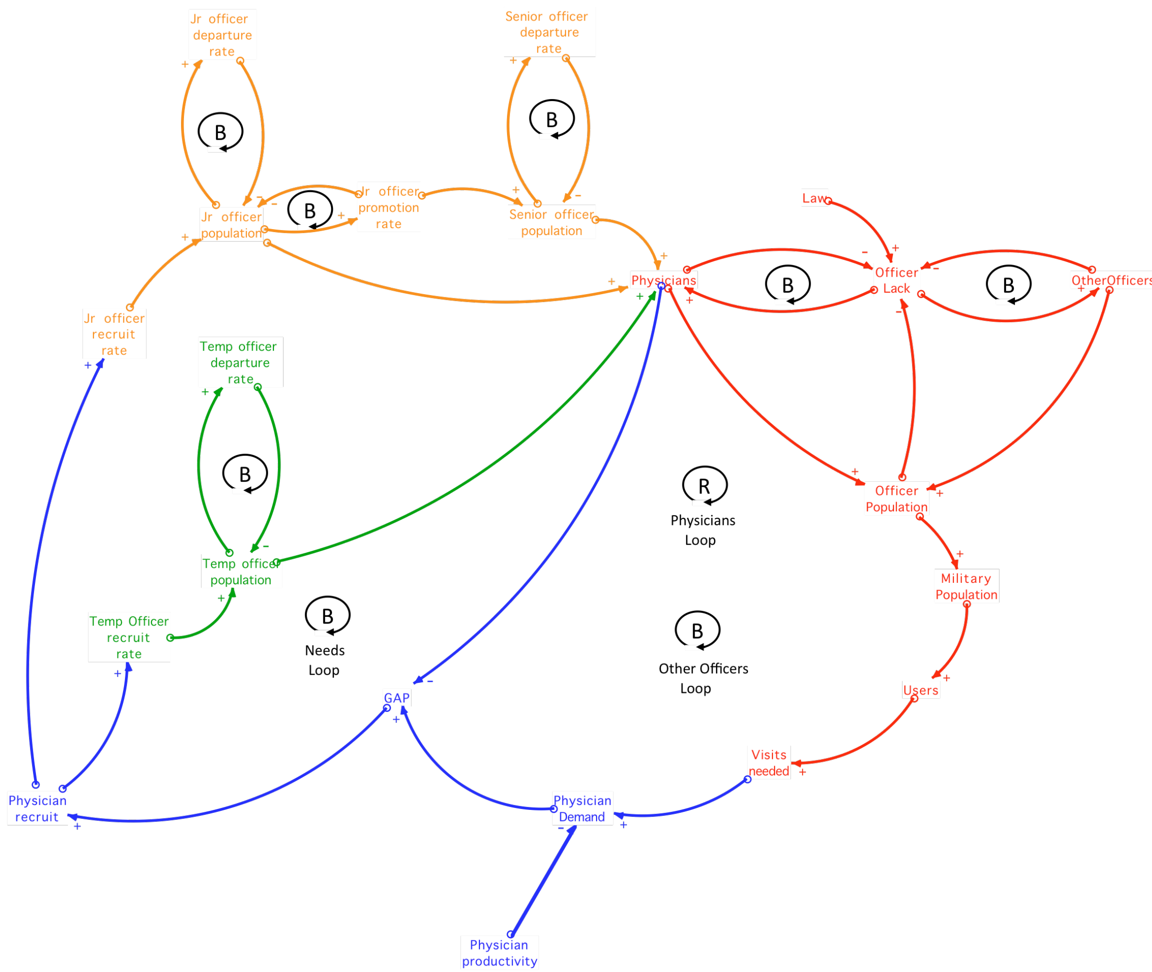
e. Needs

The needs causal-loop diagram (Figure 24) is the union of all causal loops described above with a modification in function of an additional new demand structure that indicates the relation between the number of visits needed, physician productivity, and the *GAP* between the existent number of physicians and the number of physician demanded.

Needs Loop is a negative loop that has the goal of reaching *Physician Demand*, which is changed by *Physician productivity* in the opposite direction and by *Visits needed* in the same direction. For example, increases in the number of visits needed lead to increases in *Physician Demand,* and increases in *Physician productivity* lead to a decrease in *Physician Demand.*

The stock-and-flow diagram representing the final model is the union of the models explained above, where some variables are added to allow physician demand and *GAP* calculation. To simplify the visualization, it is divided into parts such as career, temporary, users, demand, and needs models.

Figure 24 Needs causal-loop diagram



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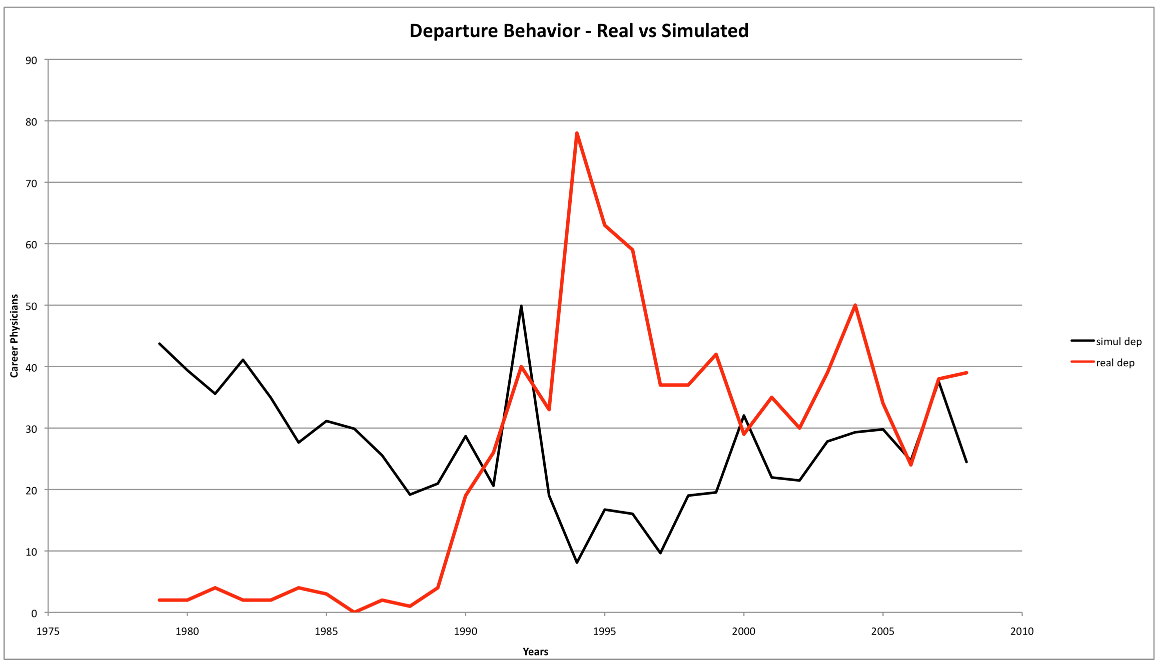
IV. BEHAVIOR REPRODUCTION, SENSITIVITY ANALYSIS, AND SIMULATION

A. BEHAVIOR REPLICATION

Though Sterman (2000) states that all models are wrong and thus validation is impossible, on the other hand he comments that testing the alternatives helps recognize the best model available for supporting and making decisions.

Using old data that has already generated departure behavior is the best way to test the real-world performance of the system and to verify qualitatively and quantitatively whether the model reproduces accurate departure behavior over time.

Figure 25 Career departure-behavior test

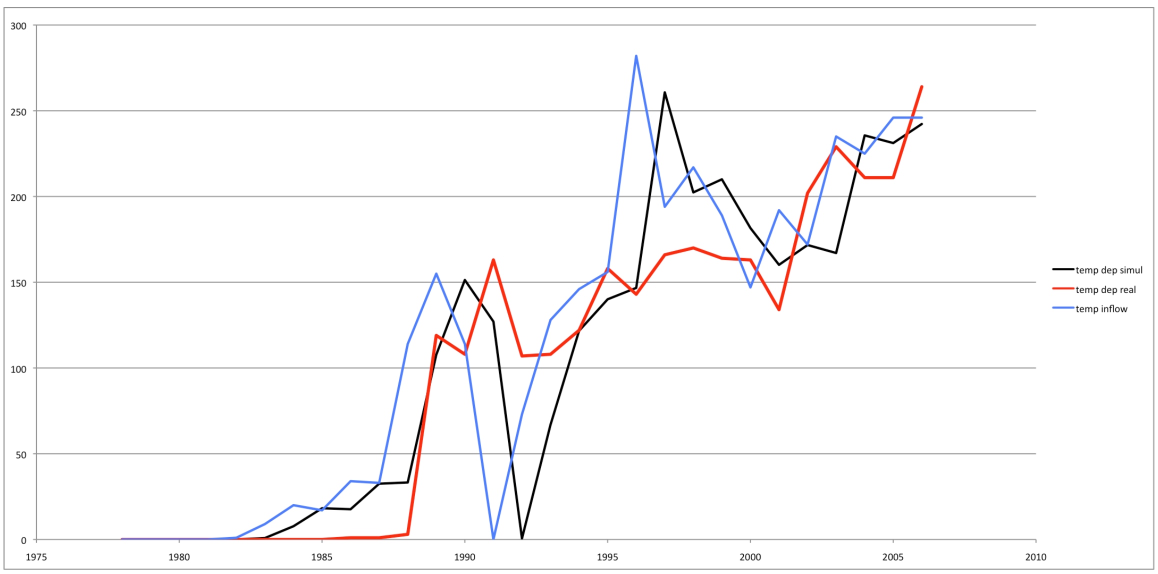


Actual career departure behavior was lower in the period from 1978 to 1988 (*real dep* in Figure 25) than the model results indicate (*simul dep* in Figure 25), but it is more than the model shows in the period from 1988 to 2000. The explanation for this difference is that before 1985 Brazil was led by a military government, and in 1988 a new federal constitution changed many aspects of Brazilian military rights and duties. Therefore, the real departure data shows a higher variability than the model result.

Additionally, temporary-officer-physician departure behavior (Figure 26) shows an increasing trend over time following recruitment increase. As explained earlier, the temporary-officer group has two main sources: draft input and volunteers. Those recruited with the draft may leave the system just after the one-year obligation period and this is the expected behavior that the model reflects. In reality, however, departure behavior increases after 1988 as a consequence of the new constitution.

In 1991, there was no recruiting for career and temporary officers, possibly because of the low visibility of health-system needs.

Figure 26 Temporary departure-behavior test



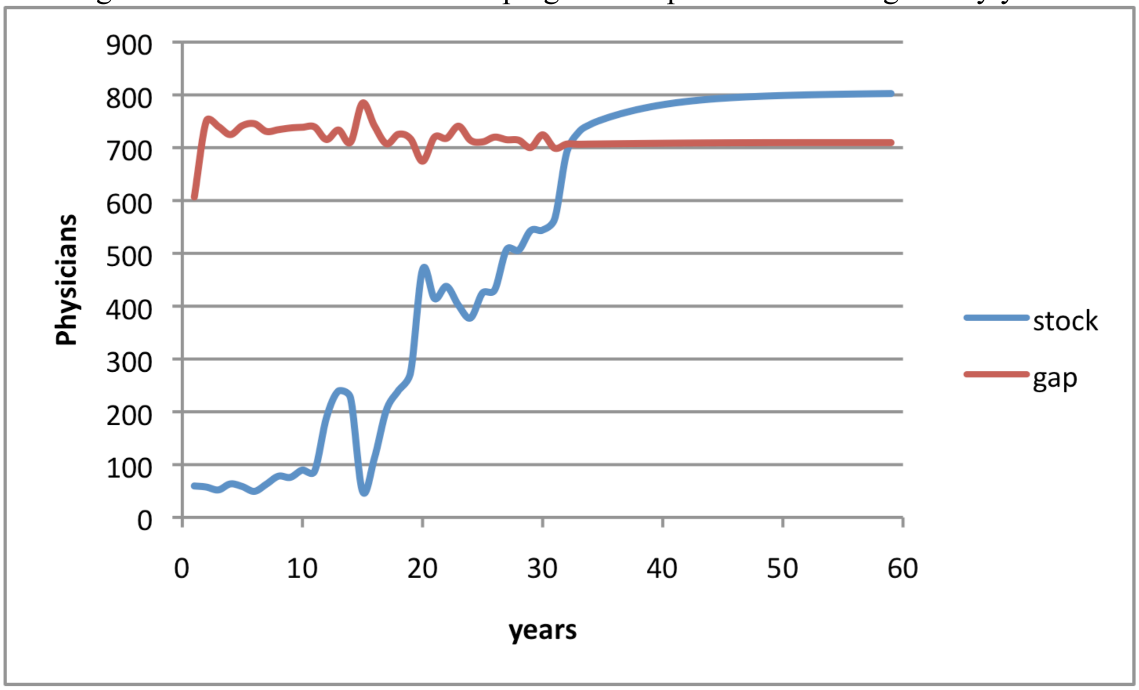
The temporary departure-behavior model follows real departure-behavior trends.

B. SENSITIVITY ANALYSIS

Behavior-mode sensitivity is a type of sensitivity analysis (Sterman 2000) used to verify how a parameter influences system behavior when set to the highest and lowest values. The method consists in changing one parameter at a time over a reasonable range and verifying how it influences the results of the model, keeping the other parameters fixed (*ceteris paribus*).

The results observed were physician stock, average physician experience acquired in the system, and the gap between physician stock and the demand for physicians. The parameters were set to default, i.e., the last observation.

Figure 27 Model results keeping the last parameters through thirty years



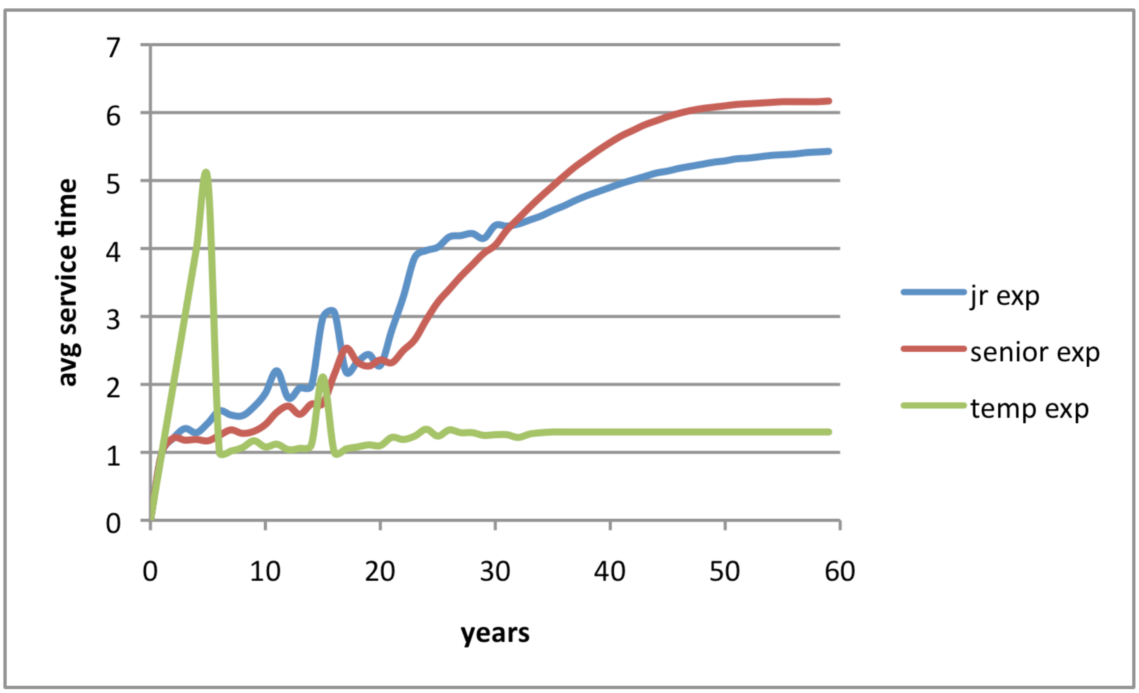
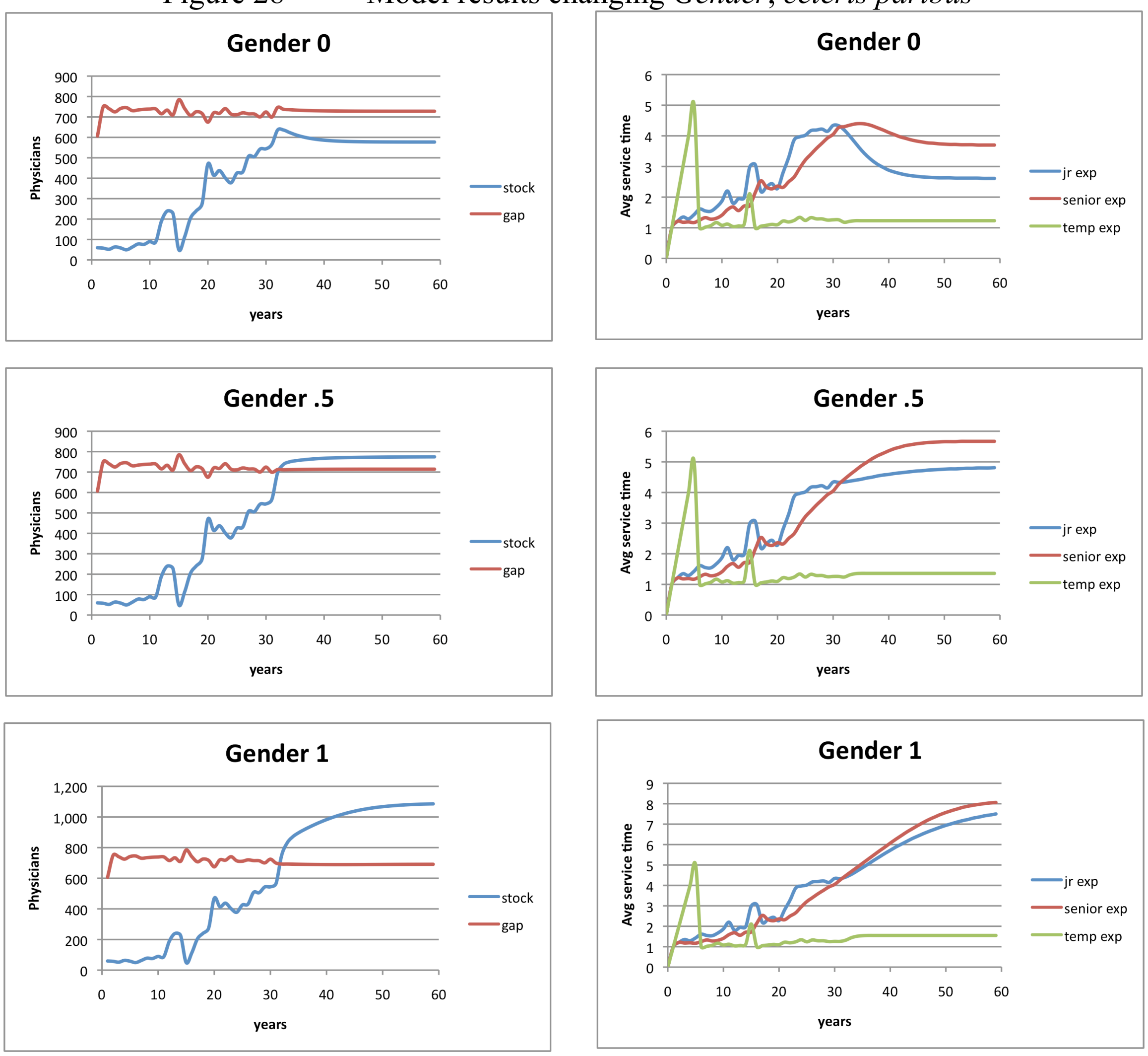


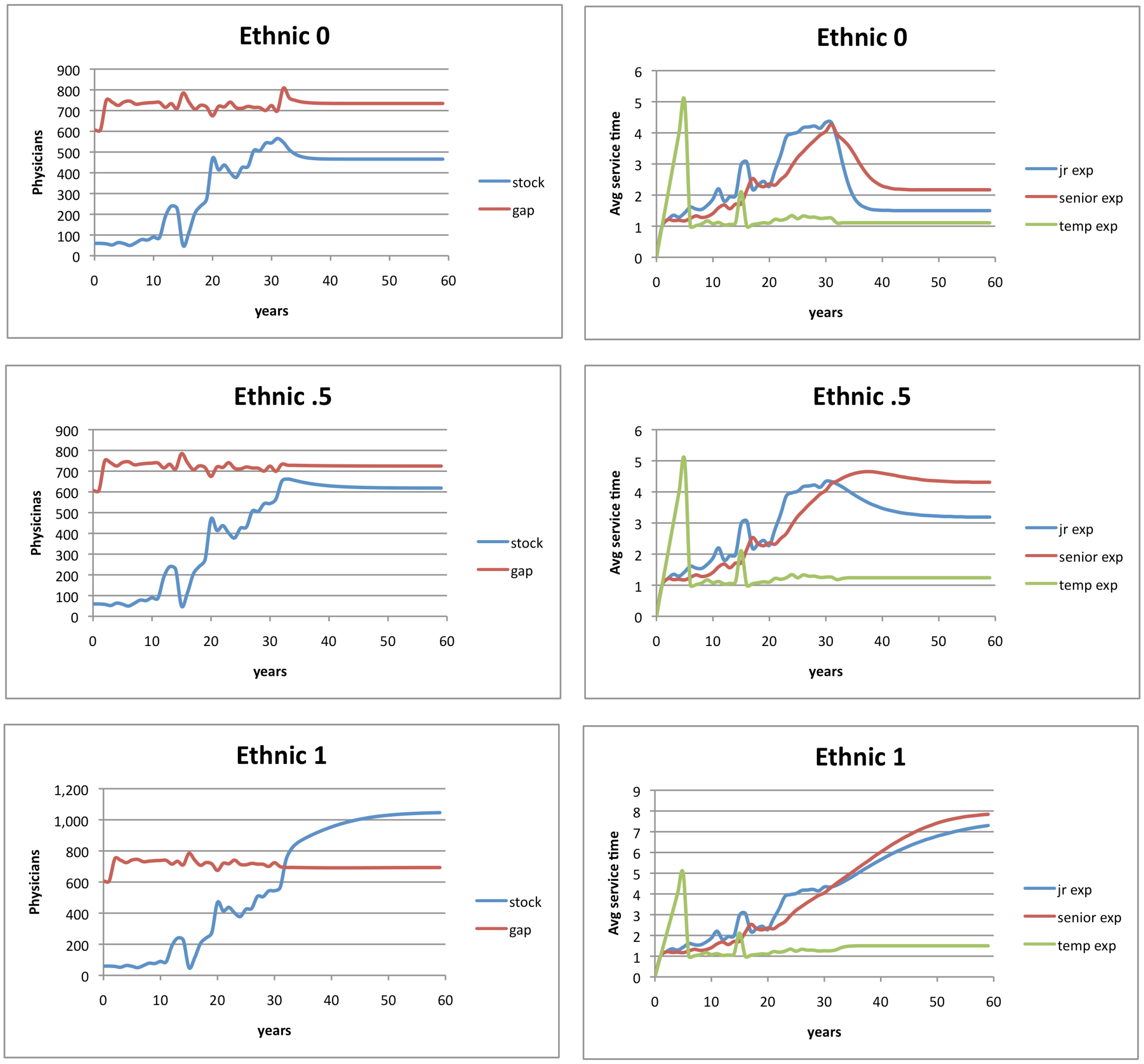
Figure 27 shows the possible outcomes if the parameters used to simulate thirty years are the last observed values. There is a trend to keep the gap near 700 physicians, i.e., demand for medical visits would reflect almost 700 additional physicians than there are in stock. Physician stock might stabilize near 800 physicians and physician service time or experience in the system would be almost 5.3 years for a junior officer, six years for a senior officer and one year for a temporary physician.

Figure 28 Model results changing *Gender*, *ceteris paribus*



The model results using only the parameter *Gender* are shown in Figure 28. They clearly display different results when the composition of the cohort varies according to the variable *Gender*, from 100% male or male majority and female minority (Gender = 0) to 100% female or female majority and male minority (Gender = 1).

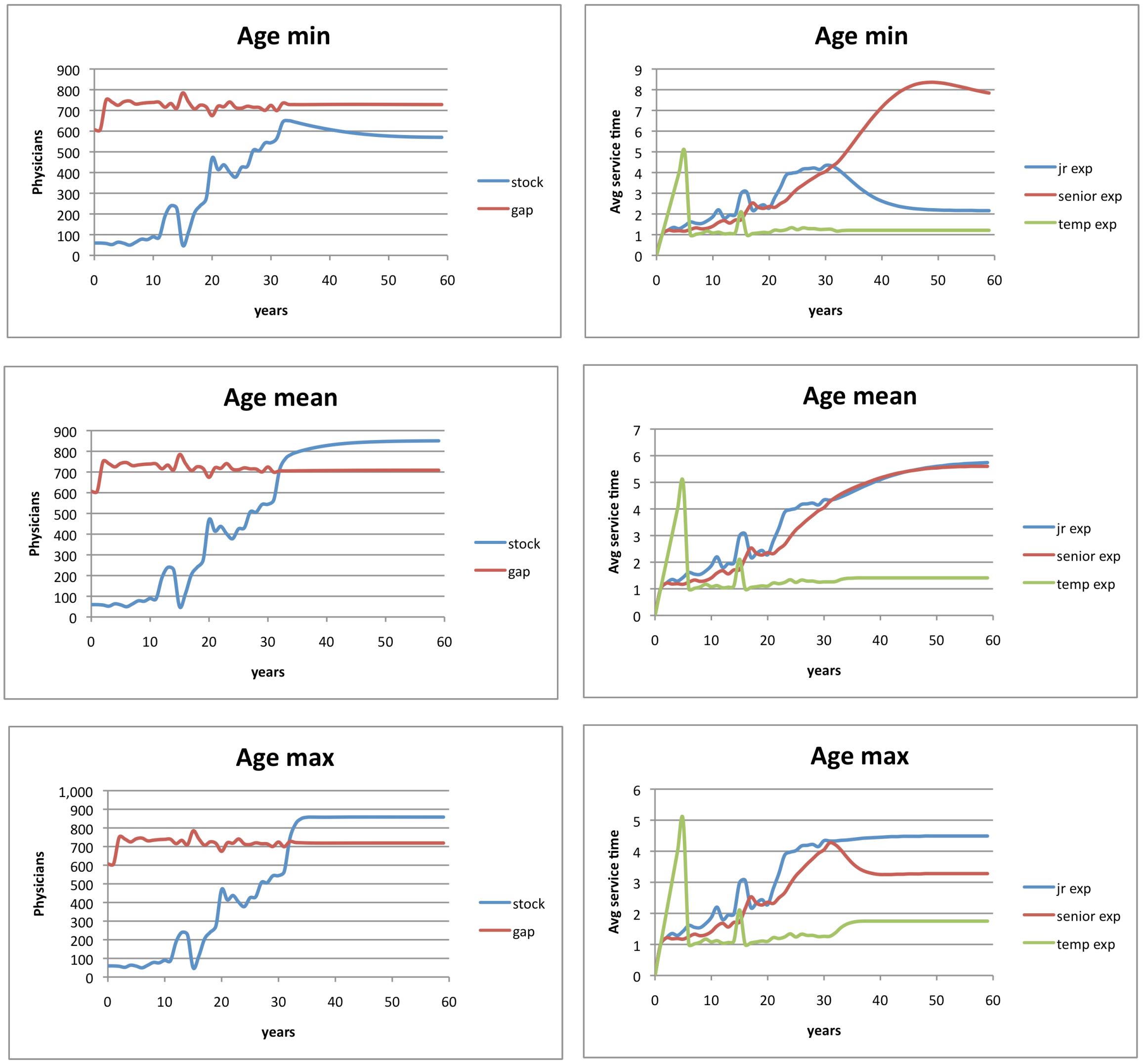
Figure 29 Model results changing *Ethnic*, *ceteris paribus*



When the parameter *Ethnic* is varied, the results change in a similar way to the variable *Gender*. Here, if the majority is made of the white ethnic group, the variable equals to 1. If the majority is mixed ethnic and the minority is white the variable equals to 0.

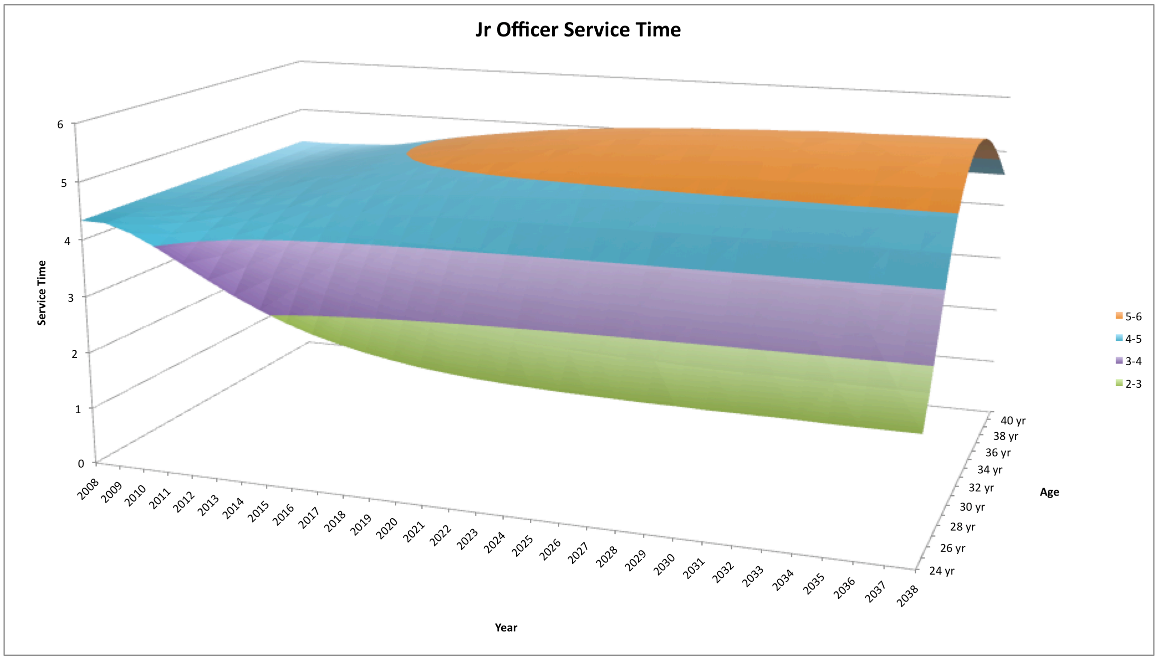
The model also shows the possible behavior of the system as a function of age (Figure 30). With this test, we verify model behavior, as well as possible policies that must be changed or redesigned to reduce undesirable behavior.

Figure 30 Model results changing *Age*, *ceteris paribus*



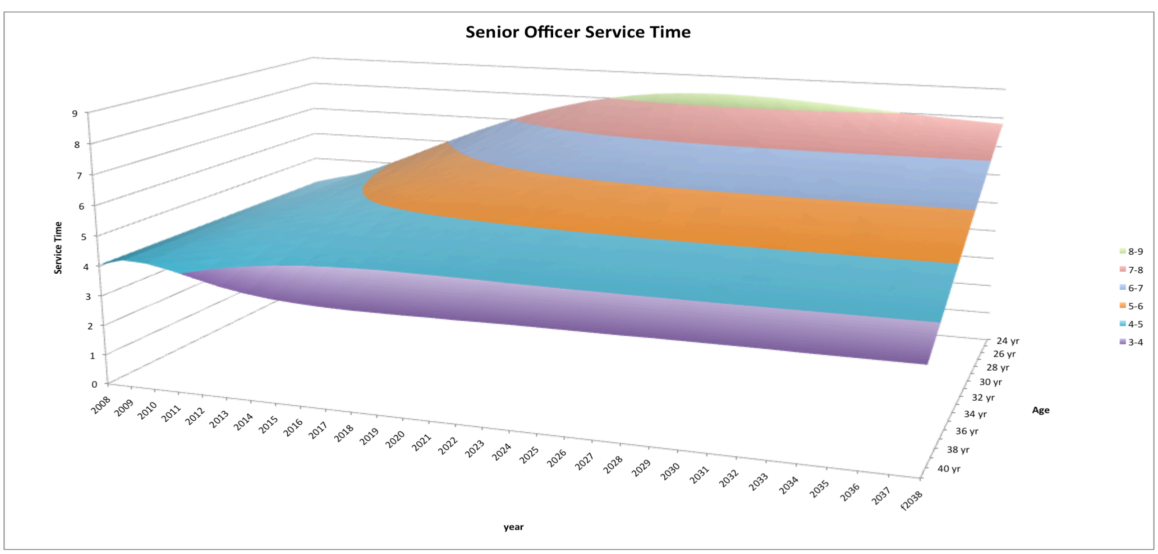
Another sensitive analysis test was done to verify service-length changes as a function of the allowed recruitment-age range for career officers, Figure 31. The age values that caused the longest service-time results are used in a simulation scenario in the next section.

Figure 31 Junior-officer service-time behavior by changing recruitment age



Senior-officer service-time behavior is different from that of junior officers, i.e., different retentions for each group could result from the same recruitment age. Figure 32 shows senior-officer service length in function of recruitment age (the age axis is reversed to facilitate visualization).

Figure 32 Senior-officer service-time behavior by changing recruitment age



The temporary-officer service-time behavior (Figure 33) shows an expected behavior for temporary officers in the function of age due to the maximum eight years of service allowed.

With the knowledge of how parameters affect system behavior, it is possible to simulate the model over time to verify trends and behaviors for different scenarios.

Figure 33 Temporary-officer service-time behavior by changing recruitment age

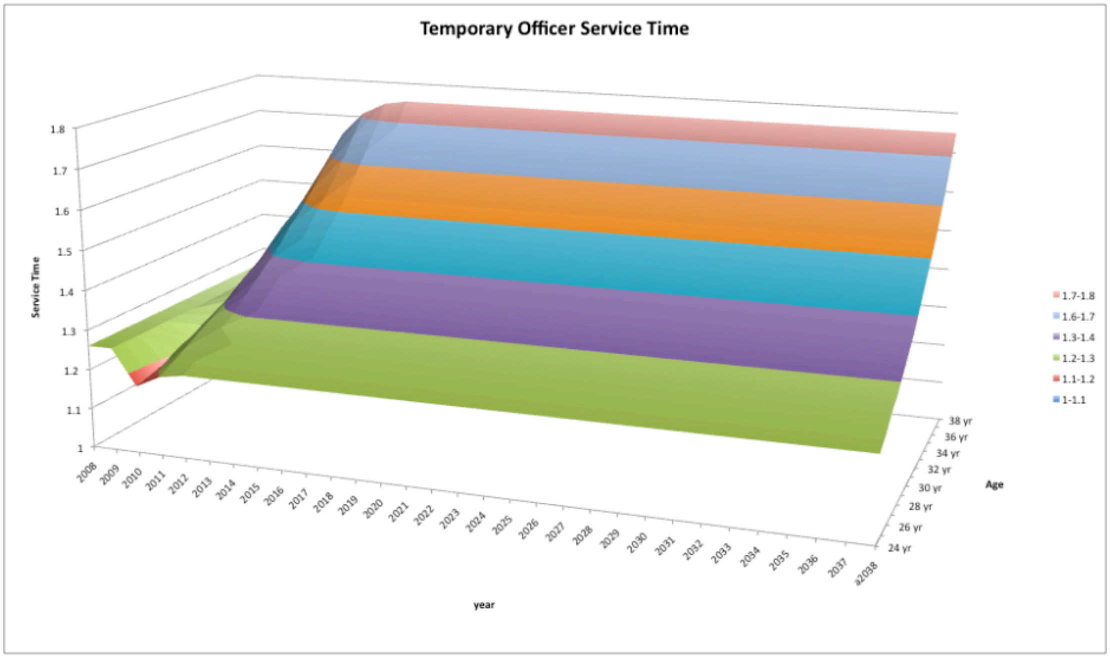
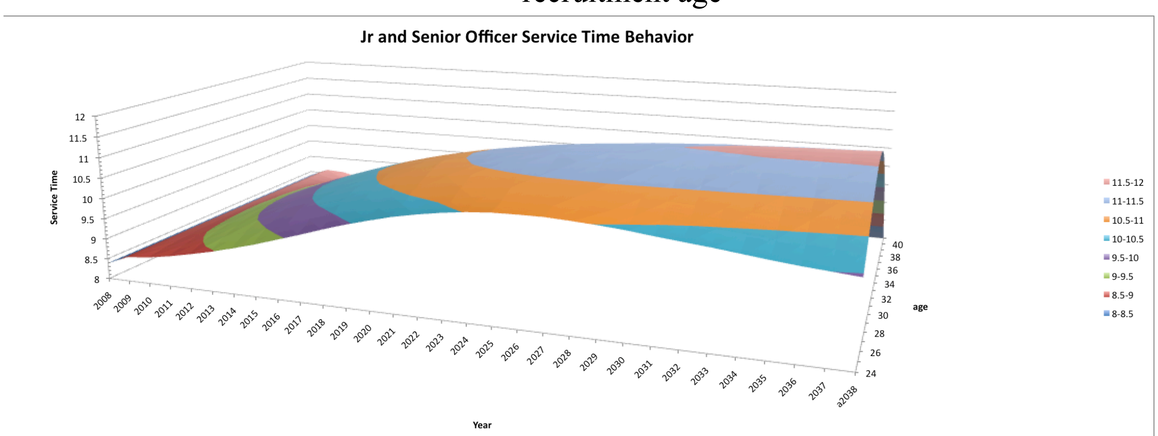


Figure 34 Junior- and senior-officer physician service-time behavior by changing recruitment age



C. SIMULATION

In addition to building models, one can develop interfaces to simulate the model. The interface built for this research has the appearance of a flight simulator (Figure 35) that allows the simulation to be monitored and parameters to be changed over time.

The model was developed to keep the historical data from 1978, i.e., simulate system behavior using real parameters until 2008, and to allow the input of new data from 2008 to 2038.

To predict recruitment numbers and officer departure over time, a future scenario or a goal must be defined. This research explores two scenarios for developing possible trends. The first is based on the assumption that there are no training limits and the Brazilian market is favorable for supplying the military with physicians needed. The second scenario uses the recruitment quantity for temporary officers and the last desired recruitment quantity defined for the national exam for career officers. It assumes that the supply physician market has enough physicians to fulfill the desired calculated quantity. Each scenario is analyzed with two parameters of configuration:

- The first is based on parameter distribution (Table 10 and Table 11) and shows possible system behavior over the next thirty years if the market and recruitment policies supply the system with average characteristics.

- The second is to input the variables in such a way as to maximize the time that a physician stays as a military, i.e., this visualization is a possible driver for future recruitment and retention polices. As a consequence, an increase in the stock of physicians is expected. The parameter values for this configuration are defined by the recruitment-age range that maximizes service length for junior- and senior-officer physicians (Figure 31 and Figure 32) and temporary-officer physicians (Figure 33). To simulate under these parameters, an assumption of more than eleven years and three months for career officers and one year and six months for temporary officers was used. The configuration for gender and ethnicity were the values that maximize service time, as shown in Figure 28 and Figure 29, above.

Table 10 Career-officer physician parameter distribution

Variable	Mean	Std.Dev.	Min	Max
Age	28.58953	2.766512	24.0137	42.41096
Gender	.2174535	.4126612	0	1
Ethnic	.5901583	.249118	0	.9047619

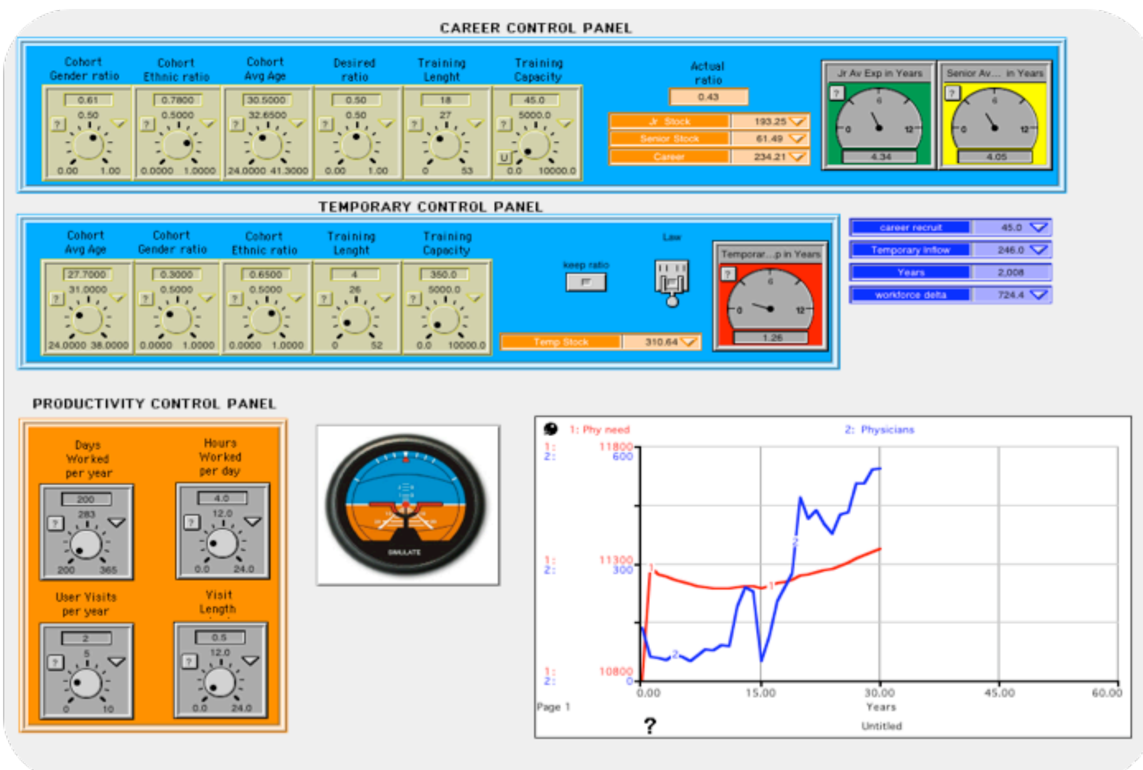
Source: COMGEP

Table 11 Temporary-officer physician parameter distribution

Variable	Mean	Std.Dev.	Min	Max
Age	27.69513	3.034225	24	37.9726
Gender	.2236589	.4167534	0	1
Ethnic	.3383668	.2236531	0	.6495727

Source: COMGEP

Figure 35 Simulator control panel



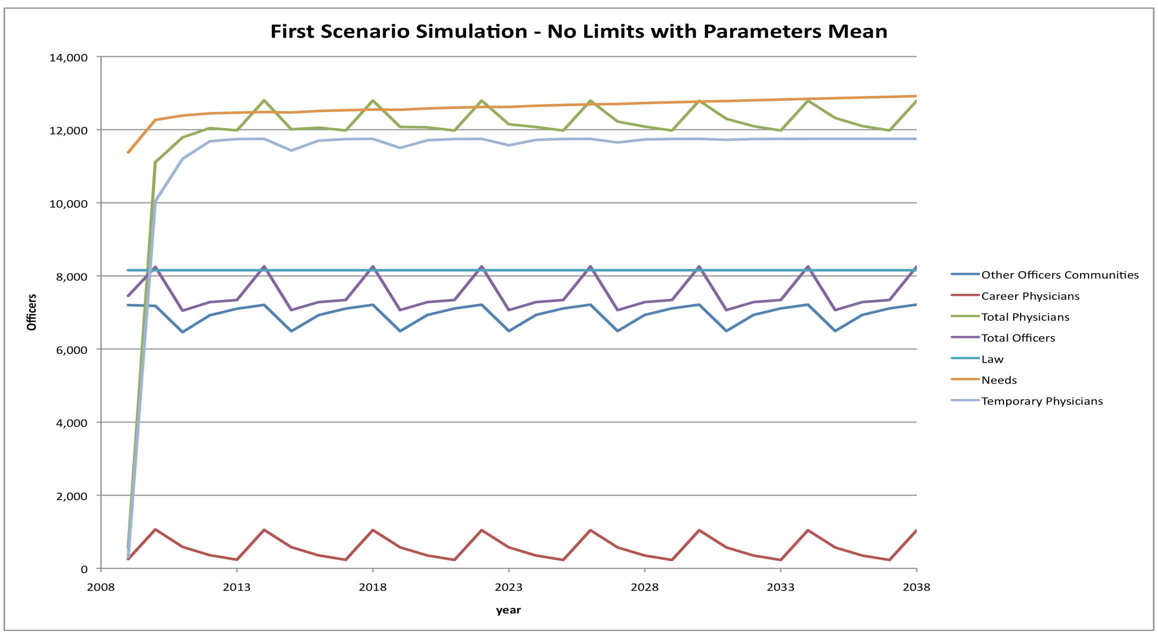
1. First Scenario: No limits

a. Average Parameters

The simulation uses the assumption that there is no limit to recruitment, and training the physician to be an officer (Figure 36). The *Career Officer Law* constraint is reached several times because of system delay in balancing officer quantity. The delay is caused by overall officer-departure behavior. There is a tradeoff between other officer communities and career physicians as the model attempts to reduce the gap between total physician stock and demand.

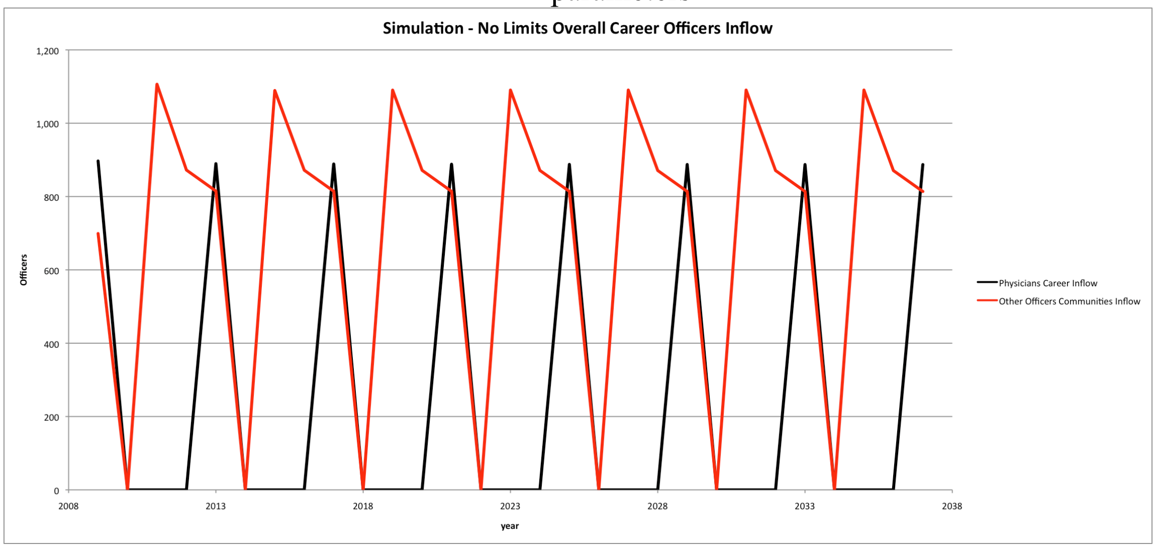
The number of temporary officers increases rapidly to reach the goal and, with career officers, make the total number of physicians overshoot needs in function of the delay caused by departures, as explained previously. As the physician total reaches the goal, the model reduces the overall-physician inflow to allow for an increase of other-officer inflow to return to the previous quantity. This causes a critical reduction of career-officer physicians. This system behavior causes an inflow of career physicians, which will cause the *Law* constraint to overshoot again and a new cycle initiates to reach equilibrium.

Figure 36 Simulation: no limits using parameters mean



The temporary-officer inflow in a no-limits scenario is the maximum needed or supplied by the market. The career-officer physician inflow follows the behavior shown in Figure 37, as well the other-officer communities' inflow. The no-limits scenario leads to a medical workforce with a high number of temporary physicians and almost 45% of the career inflow as career physicians in repetitive events during the thirty-year timeframe. This inflow is a result of the system's trying to keep the stock of career physicians to a quantity that allows for promotion flow.

Figure 37 Simulation: no limits, overall career-officer inflow using averaged parameters



b. Maximized Results

Setting the recruitment-age values for career officers to between twenty-eight and thirty-three years old and above thirty-three for temporary physicians leads to the desired behavior (Figure 33 and Figure 34) by extending service length and, in the same way, setting the gender value to one (Figure 28) and the ethnic variable to maximum value (Figure 29).

Adopting average parameters in the simulation, *Temporary Physicians* increases rapidly to meet the *Needs*. The main difference here is the tradeoff between *Other Officers Communities*, *Temporary Physicians* and *Career Physicians*. The cause of this behavior is an increase in *Career Physicians* retention and the need to keep the career stocks supplied with enough physicians to allow for the promotion flow that results in an overshoot of *Needs* and a *Temporary Physicians* trade-off, as well as an increase *in Total Career Officers* and reduction in *Other Officers Communities* in function of the trade-off, as shown in Figure 38.

The temporary-officer inflow equals the number of physicians needed, and as the *Physician Career Inflow* occurs, the temporary inflow decreases by almost the same amount. The *Other Officers Communities Inflow* decreases as shown in Figure 39.

Figure 38 Simulation: no limits, using parameters to maximize results

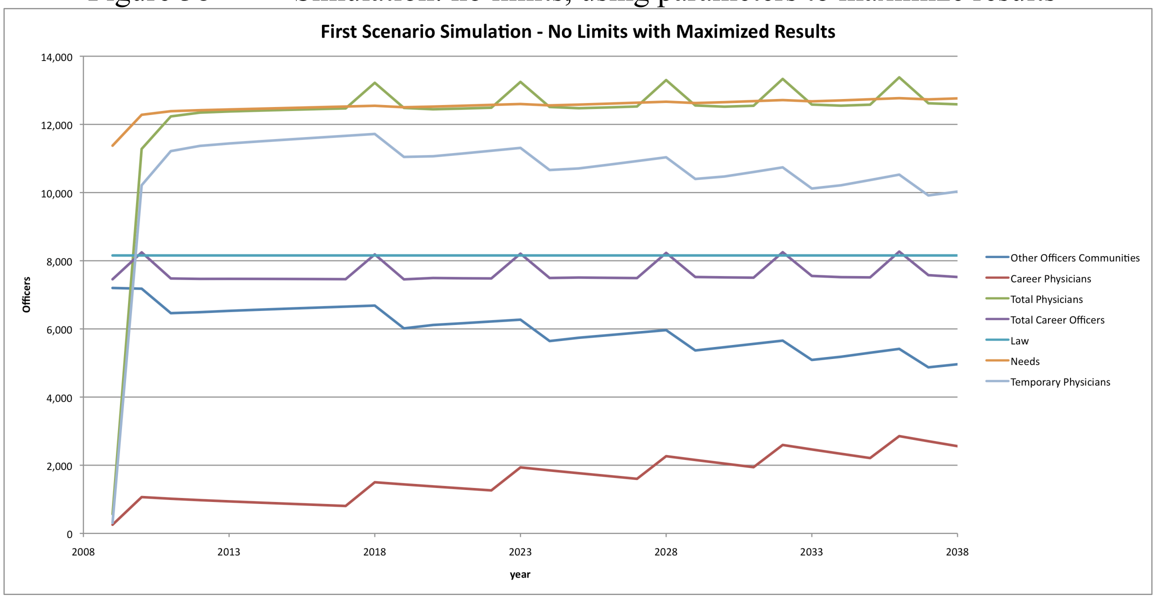
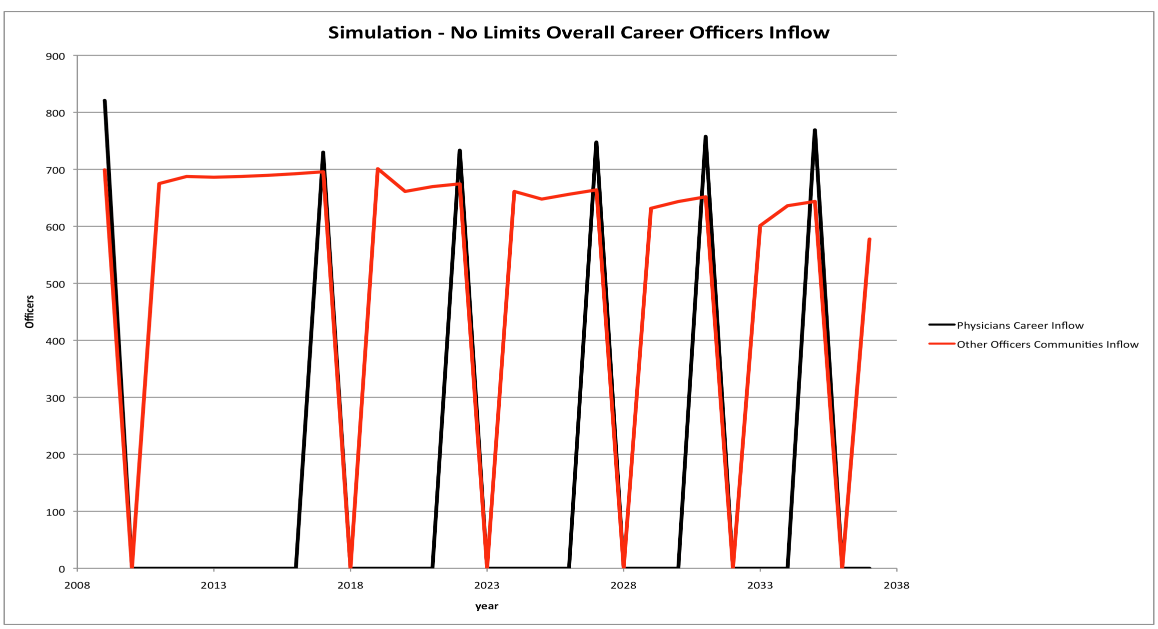


Figure 39 Simulation: no-limits, overall career-officer inflow using parameters to maximize results



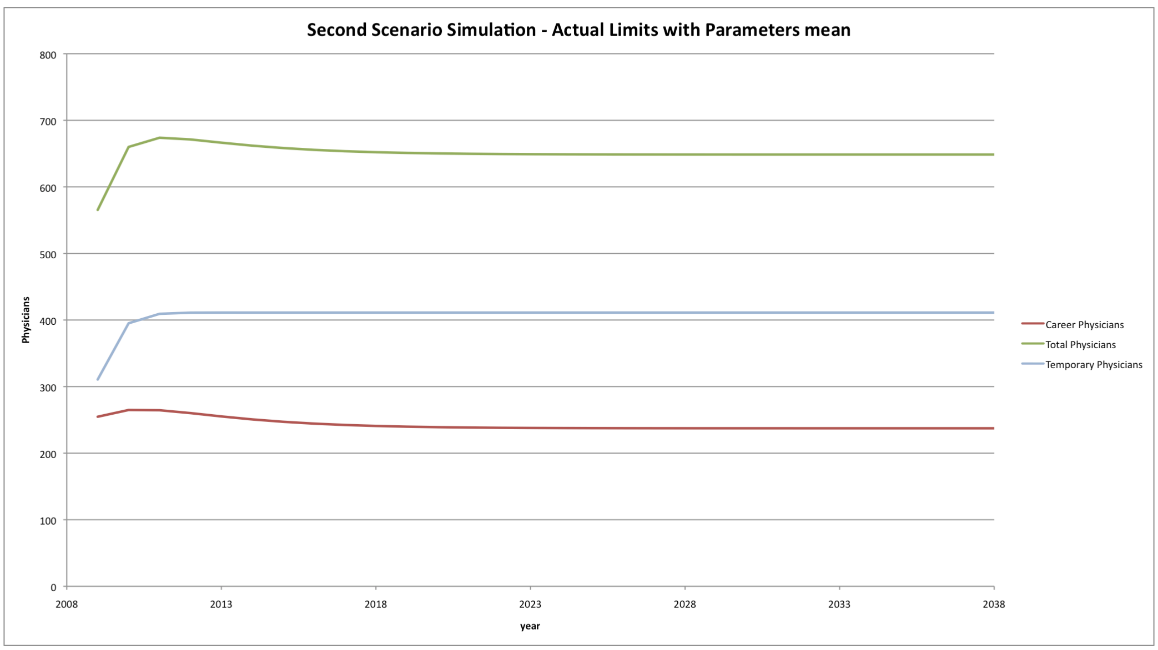
2. Second Scenario: Actual Limits

The last national exam to recruit career officers tried to contract 96 physicians in the National Physician Market and almost 350 temporary physicians. These values were used in simulation as the training capacity for each group (Figure 35).

a. Average Parameters

The average parameters used in the second scenario were the same used in the first scenario (Table 10 and Table 11). The simulation results show that changes are very low and the system stabilizes rapidly (Figure 40). The main consequence of this kind of policy is that the gap between the desired physician quantities that are demanded by system users never declines. The inflow stabilizes in the defined quantities, since that represents the maximum allowed in the system contract.

Figure 40 Second scenario simulation: actual limits using averaged parameters

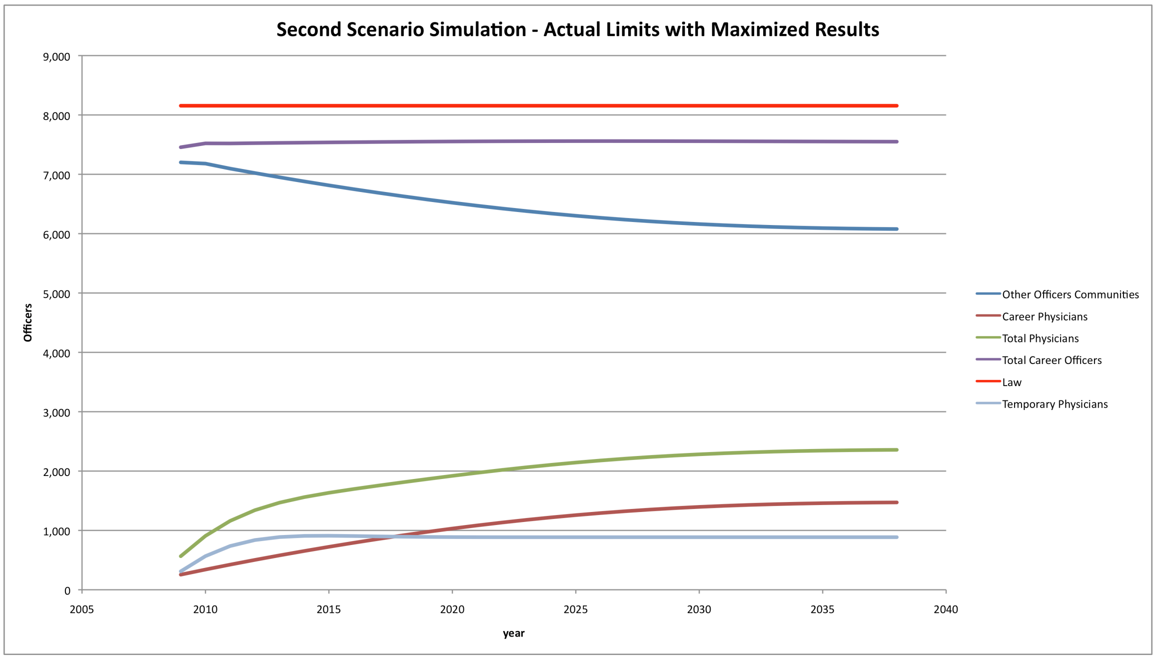


b. Maximized Results

With the parameters set to values that maximize the results, the system shows tradeoffs between *Other Officers Communities* and *Career Physicians*. The simulation results show that *Total Career Officers* reaches a stabilized level while *Other*

Officer Communities decreases and the *Career Physicians* increases. The inflow of the system is constant for physicians but lowers for *Other Officer Communities* as *Career Physicians* increases.

Figure 41 Second scenario simulation: actual limits using parameters to maximize results



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V. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

This research contributes to understanding how physicians in the Brazilian Air Force health system behave over time regarding their promotion and departure of the force. System-dynamics modeling, together with multivariate regression, allows using past physician behavior to predict future behavior and to design recruitment trends for the next thirty years.

Research questions drove the development of the model and helped understanding the future manpower needs of the Brazilian Air Force health system. The results of the first scenario simulation can help the design of retention, recruitment, and departure policies. The second scenario shows that the current policies need to be revised to satisfy the expectations of system users.

B. CONSIDERATIONS FOR FUTURE STUDIES

System-dynamics modeling with multivariate regression allows the measurement and simulation of complex systems. A more precise simulation is possible with these combined theories. The health-system model revealed a need for improvement, and questions that arose during this research would be useful in possible future research:

- How does civilian-market supply and demand affect recruitment and retention behaviors and processes?
- What is the physician market in different regions and how do the interactions between market cultures affect the overall system?
- What behaviors characterize physician specialties, and what are the interactions between them?

These questions and more must be answered to pursue future research and extension of the system dynamics and multivariate models developed in this thesis.

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LIST OF REFERENCES

Abdel-Hamid, T. K. (1984). *The dynamics of software development project management: An integrative system dynamics perspective*. Unpublished PhD Thesis. Massachusetts Institute of Technology. Cambridge, MA.

Bartholomew, D. J. (1974). Stochastic models and their application: a review. In D.J. Clough, C.G. Lewis and A.L. Oliver (Eds.), *Manpower Planning Models* (pp. 81-90). London, UK: English Universities Press.

Brazilian Air Force Career National Exams (2007). Retrieved September 2, 2008, from http://www.fab.mil.br/portal/capa/index.php?id=6&page=mostra_concurso

Brazilian Air Force Officers Distribution Regulation (2008). *Presidency of the Federative Republic of Brazil*. Retrieved December 12, 2008, from https://www.planalto.gov.br/ccivil_03/_ato2007-2010/2008/decreto/d6549.htm

Brazilian Institute of Geography and Statistic Population Demographic Data (2000). Retrieved in January 4, 2009, from http://www.ibge.gov.br/series_estatisticas/tema.php?idtema=6

Brazilian Health Minister (2002). *Portaria nº 1101*. Retrieved in September 2, 2008, from http://dtr2001.saude.gov.br/sas/PORTARIAS/Port2002/Gm/GM-1101.htm

Bueno, R. L. & Pieruccini, M. C. (2005). Brazilian Medical Schools. In CFM Study. Retrieved September 2, 2008, from http://www.portalmedico.org.br/include/biblioteca_virtual/abertura_escolas_medicina/007.htm

Graunt, J. (1662). Natural and political observations mentioned in a following index, and made upon the bills of mortality. In *Edstephan*. Retrieved December 1, 2008, from http://www.edstephan.org/Graunt/bills.html

Koopman, M. E. (2006, January). Creating innovative career paths [Eletronic version]. *CNA Research Memorandum D0013254.A1.*

McClean, S. (1988). Manpower planning models and their estimation. *European Journal of Operational Research, 51,* 177-187. North Holland: Elsevier.

Mooney, D. & Swift, R. (1999). *A course in mathematical modeling*. The Mathematical Association of America.

Stata: Data Analysis and Statistical Software (Version 10) [Computer software]. (2008).

Stella (Version 9.1) [Computer software]. (2009).

Sterman, J. D. (2000). *Business dynamics, system thinking and modeling for the complex world*. Irwin McGraw & Hill.

Teigland, C., & Hewig, L. (1990). Projecting workforce needs in government : The case of New York state. In M. London, E. S. Bassman, J. P. Fernanez (Eds.), *Human Resource Forecasting and Strategy Development* (pp. 41-51). New York: Quorum Books.

Vadja, S. (1984). *Mathematics of manpower planning*. John Wiley & Sons.

Walker, J. W. (1971). Models in manpower planning : One objective increase understanding. *Business Horizons*, Elsevier, vol. 14(2), 87-95.

Walker, J. W. (1974). Evaluating the practical effectiveness of human resource planning applications, In *Human Resource Management, 13*, (pp. 19-27).

Williams, R. (2006). OGLM: Stata module to estimate Ordinal Generalized Linear Models. In *Econpapers.* Retrieved October 23, 2008, from http://econpapers.repec.org/software/bocbocode/s453402.htm

Wooldridge, J. M. (2006). *Introductory econometrics: A modern approach*. Thompson South-Western.

World Health Organization Statistical Information System (2008). Retrieved November 10, 2008, from http://www.who.int/whosis/data/Search.jsp

Yelsey, A. (1982). Validity of human resource forecast designs. *Human Resource Planning, 5(4),* (pp. 217-224).

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